Firm Productivity Differences From Factor Markets

Wenya Cheng
University of Manchester

John Morrow†
Birkbeck College, CEP & CEPR

28 July 2017

Abstract

We model firm adaptation to local factor markets in which firms care about both the price and availability of inputs. The model is estimated by combining firm and population census data, and quantifies the role of factor markets in input use, productivity and welfare. Considering China's diverse factor markets, we find within industry interquartile labor costs vary by 30-80%, leading to 3-12% interquartile differences in TFP. In general equilibrium, homogenization of labor markets would increase real income by 1.33%. Favorably endowed regions attract more economic activity, providing new insights into within-country comparative advantage and specialization.

JEL Codes: D5, F1, O1.
Keywords: General Equilibrium, Factor Endowments, Structural Estimation, Productivity.

Acknowledgments. We thank Maria Bas, Andy Bernard, Loren Brandt, Sabine D'Costa, Fabrice Defever, Swati Dhingra, Ben Faber, Garth Frazier, Beata Javorcik, Tim Lee, Rebecca Lessem, Alan Manning, John McLaren, Marc Melitz, Dennis Novy, Emanuel Ornelas, Francesc Ortega, Gianmarco Ottaviano, Henry Overman, Dimitra Petropoulou, Veronica Rappoport, Ray Riezman, Tom Sampson, Laura Schechter, Anson Soderbery, Heiwai Tang, Dan Trefler, Greg Wright, Ben Zissimos and referees for insightful comments and especially Xiaoguang Chen. We thank participants at the HSE, UC-Davis, LSE CEP-DOM, Geography, Labor and Trade Workshops, Oxford, Nordic Development, CSAEM, Sussex, Loughborough, Warsaw School, Maynooth, Royal Economic Society, Midwest Development, Middlesex, IAB, Wisconsin, CESI, Osaka, Waseda, West Virginia, George Washington, CUNY Queens, Iowa, Chulalongkorn, ETSG, EEA, Manchester, CESifo, CORE, Essex, Southampton, Stockholm, Edinburgh, Toronto, Leuven and EIIT.
†Corresponding Author: CEP, LSE, Houghton Street, London WC2A 2AE. Email: j.morrow1@lse.ac.uk

1 Introduction

Although firms may face radically different production conditions, this dimension of firm heterogeneity is often overlooked. A number of studies document large and persistent differences in productivity across both countries and firms (Syverson, 2011). However, these differences remain largely 'some sort of measure of our ignorance'. This paper inquires to what extent the supply characteristics of regional input markets might help explain such systematic productivity dispersion across firms, differences which remain a 'black box' (Melitz and Redding, 2014). It would be surprising if disparate factor markets result in similar outcomes, when clearly the prices and quality of inputs available vary considerably. This paper models firm adaptation to such factor market variation in a general equilibrium framework. The structural equations of the model are simple to estimate and the estimation results quantify the importance of local factor markets for firm input use, productivity and welfare.

Differences between factor markets, especially for labor, are likely to be especially stark. Even the relatively fluid US labor market exhibits high migration costs as measured by the wage differential required to drive relocation and 'substantial departures from relative factor price equality' (Kennan and Walker (2011), Bernard, Redding, and Schott (2013)). Thus, free movement of factors does not mean frictionless movement, and recent work has indicated imperfect factor mobility has sizable economic effects (Topalova, 2010). Rather than considering the forces which cause workers to relocate, this paper instead inquires what existing differences in regional input markets imply for firm behavior.

We take an approach rooted in the general equilibrium trade literature to understand how local endowments impact firm behavior. We model firm entry across industries and regional markets with differing distributions of worker types, wages and regional input quality. Firms vary in their ability to effectively combine different types of labor (e.g. Bowles, 1970), and hire the optimal combination of workers given local conditions and search costs. As the ease of finding any type of worker increases with their regional supply, firm hiring depends on the joint distribution of worker types and wages. Our estimates indeed confirm that contrary to standard neoclassical models, firm hiring responds to both the wages and availability of worker types. Since each firm's optimal workforce varies by industry and region, the comparative advantage of regions varies within industry. Since industries also differ in factor intensity, local capital and materials costs also influence the comparative advantage of a region.[1] Firms thus locate in proportion to the cost advantages available.[2]

[1]Here the comparison of firms *within* country isolates the role of factor markets from known international differences in production technology: e.g. Trefler (1993), Fadinger (2011) and Nishioka (2012).

[2]Effective labor costs are driven by the complementarity of regional endowments with industry technology, and the paper refers to these additional real production possibilities as 'productivity'.

But are these differences economically important? To quantify real world supply conditions, we use the model to derive estimating equations which fix: 1) hiring by wage and worker type distributions, 2) substitution into non-labor inputs, 3) firm location in response to local factor markets, and 4) the role of heterogeneous factor markets on real income. The estimation strategy combines manufacturing and population census data for China in the mid-2000s, a setting which exhibits substantial variation of a large number of labor market conditions (see Figures 5.1b, 5.2, Appendix). By revealing how firm demand for skills varies with local conditions, the model quantifies the unit costs for labor across China when firms care about both wages and worker availability in the presence of hiring frictions. The estimates imply within industry interquartile differences in effective labor costs of 30 to 80 percent. A second stage estimates production technology, explicitly accounting for regional costs and substitution into non-labor inputs. Once substitution is accounted for, labor costs result in interquartile productivity differences of 3 to 12 percent, and local factor markets explain 6 to 30 percent of the variance of productivity.[3,4]

In contrast to studies which look solely at TFP differences, this paper pushes further into the microeconomic foundations of how local factor markets impact input usage and thereby influence productivity. It also fully specifies consumer behavior and industrial organization to arrive at a welfare analysis that considers the supply and entry decisions of firms in response to distortions.[5] The model implies that homogenizing worker distributions and wages across factor markets would increase real incomes by 1.33 percent. Furthermore, we show that in general equilibrium, economic activity tends to locate where regional costs are lowest, as supported by the data.

We conclude this section by relating the paper to existing work. The paper then continues by laying out a model that incorporates a rich view of the labor hiring process. The model explains how firms internalize the local distribution of worker types and wages to maximize profits, resulting in an industry specific unit cost of labor by region. Section 3 places these firms in a general equilibrium, monopolistic competition framework, and addresses the determination of factor prices, welfare and firm location. Section 4 explains how the model can be estimated with a simple nested OLS approach, which allows for well developed techniques such as instrumental variable estimators to be used. Section 5 discusses details of the data, while Section 6 presents model estimates and uses them to explain the effect of different regional input markets on firm hiring, productivity, location and welfare. Section 7 concludes.

Related work. This paper models firms which depend on local factor markets in a fashion typified by the Heckscher-Ohlin-Vanek theory of international trade (e.g. Vanek (1968), Bernard, Redding, and Schott (2007)). The departures from H-O-V in the model relax assumptions about

[3]These substantial differences underscore Kugler and Verhoogen (2011): since TFP is often the 'primary measure of [...] performance', accounting for local factor markets might substantially alter estimates of policy effects.

[4]Put together, capital and materials frictions explain a similar range of productivity differences.

[5]TFP differences are not alone sufficient to induce distortions in general equilibrium (Dhingra and Morrow, 2012).

perfect labor substitutability and homogeneous factor markets, which quantifies the role of local labor markets and input costs. On the product market side, we consider many goods as indicated by Bernstein and Weinstein (2002) as appropriate when considering the locational role of factor endowments. At the industry level, we follow Melitz (2003), but add free entry by firms across regions. A firm's optimal location depends on local costs which arise from the regional distribution of worker types and wages, but competition from firms which enter the same region prevent complete specialization. The model quantifies the intensity of firm entry and shows that within country, advantageous local factor markets are important for understanding specialization patterns.[6]

Recently, both Borjas (2013) and Ottaviano and Peri (2012) have emphasized the importance of more complete model frameworks to estimate substitution between worker types. In distinction to the labor literature, our interest is firm substitution across factor markets. Dovetailing with this are theories proposing that different industries perform optimally under different degrees of skill diversity. Grossman and Maggi (2000) build a theoretical model explaining how differences in skill dispersion across countries could determine comparative advantage and global trade patterns. Building on this work, Morrow (2010) models multiple industries and general skill distributions, and finds that skill diversity explains productivity and export differences in developing countries.

The importance of local market characteristics, especially in developing countries, has recently been emphasized by Karadi and Koren (2012). These authors calibrate a spatial firm model to sector level data in developing countries to better account for the role of firm location in measured productivity. Moretti (2011) reviews work on local labor markets and agglomeration economies, explicitly modeling spatial equilibrium across labor markets. Distinct from this literature, we take the outcome of spatial labor markets as given and focus on the trade offs firms face and the consequences of regional markets on effective labor costs and firm location.[7,8]

Although we are unaware of other studies estimating model primitives as a function of local market characteristics, existing empirical work is consonant with the theoretical implications. Iranzo, Schivardi, and Tosetti (2008) find that higher skill dispersion is associated with higher TFP in Italy. Similarly, Parrotta, Pozzoli, and Pytlikova (2014) find that diversity in education leads to higher productivity in Denmark. Martins (2008) finds that firm wage dispersion affects firm performance in Portugal. Bombardini, Gallipoli, and Pupato (2012) use literacy scores to show

[6]In spirit, this result is akin to Fitzgerald and Hallak (2004) who study the role of cross country productivity differences in specialization. In this paper, differences in unit labor costs predict specialization across regions.

[7]Several papers have explored how different aspects of labor affect firm-level productivity. There is substantial work on the effect of worker skills on productivity (Abowd Kramarz and Margolis (1999, 2005), Fox and Smeets (2011)). Other labor characteristics that drive productivity include managerial talent and practices (Bloom and Reenen, 2007), social connections among workers (Bandiera, Barankay, and Rasul, 2009), organizational form (Garicano and Heaton, 2010) and incentive pay (Lazear, 2000).

[8]Determinants of productivity include market structure (Syverson, 2004), product market rivalry and technology spillovers (Bloom, Schankerman, and Van Reenen, 2013) and vertical integration (see Hortaçsu and Syverson (2007) and Atalay, Hortacsu, and Syverson (2012)).

that countries with more dispersed skills specialize in industries characterized by lower skill complementarity. In contrast, this paper combines firm and population census data to explicitly model regional differences, leading to micro founded identification and estimates. The method used is novel, and results of this paper highlight the degree to which firm behavior is influenced through the availability of inputs at the micro level.[9]

Clearly this study also contributes to the empirical literature on Chinese productivity. Ma, Tang, and Zhang (2014) show that exporting is positively correlated with TFP and that firms self select into exporting which, ex post, further increases TFP. Brandt, Van Biesebroeck, and Zhang (2012) estimate Chinese firm TFP, showing that new entry accounts for two thirds of TFP growth and that TFP growth dominates input accumulation as a source of output growth. Hsieh and Klenow (2009) posit that India and China have lower productivity relative to the US due to resource misallocation and compute how manufacturing TFP in India and China would increase if resource allocation was similar to that of the US. Brandt, Tombe, and Zhu (2013) perform a more aggregate analysis of misallocation between state and non-state firms across provinces, detailing aggregate dynamic trends and finding TFP losses of approximately 20%.[10] Distinct from these studies, we focus on the internal responses of firms to detailed local conditions and carry these microeconomic firm foundations through to aggregate analyses of entry and consumer welfare in general equilibrium.

2 The Role of Local Factor Markets in Production

This section develops a model of local factor markets which impact firms' input choices, costs and productivity. Firms combine homogeneous inputs (materials, capital) and differentiated inputs (types of labor). We model variation in regional capital and material quality and detailed labor markets in which firms search for workers. When hiring, firms respond to both the wages and quantities of locally available worker types. While homogeneous inputs are mobile within industries, we take the distribution of labor endowments as given from the firm perspective and ask how observed regional supply effects firm workforce composition and productivity.[11] Our empirical strategy of using observed factor market outcomes (which can at best be only imperfectly generated by any underlying theory of factor movements) accommodates many possible influences on the distribution of factors while focusing on our core questions regarding firm behavior under the assumption that individual firms are too small to influence aggregate conditions. Here we proceed

[9]The importance of backward linkages for firm behavior are a recurring theme in both the development and economic geography literature, see Hirschman (1958) and recently Overman and Puga (2010).

[10]How the mechanisms of this paper interact with the above mechanisms is a potential area for further work and might help explain the Chinese export facts of Manova and Zhang (2012) and the different impact of liberalization across trade regimes found by Bas and Strauss-Kahn (2015).

[11]Special cases of the model include perfect factor mobility (potentially equal endowments in all regions in the absence of frictions) or equalization up to frictional input costs.

with a detailed specification of the labor hiring process, solving for firms' optimal responses to local labor market supply conditions. This quantifies the unit cost for labor by region in terms of observable local conditions and model parameters.

2.1 Searching for Workers in a Local Factor Market

Firms within an industry T face a neoclassical production technology which combines materials M, capital K and labor L to produce output. While materials and capital are composed of homogeneous units, effective labor is produced by combining $\mathbb{S}$ different skill types of workers. These different worker types are distributed unequally across regions. The distribution of worker types in region R is denoted $a_R = \left(a_{R,1}, \ldots, a_{R,\mathbb{S}}\right)$, while the distribution of wages is denoted $w_R = \left(w_{R,1}, \ldots, w_{R,\mathbb{S}}\right)$. While wages are endogenous to local factor market conditions, they are exogenous from the perspective of firms and workers. Workers do not contribute equally to output. This occurs for two reasons. First, each type provides an industry specific level of human capital $\underline{m}_i^T$. Second, when a worker meets a firm, this match has a random quality $h \geq 1$ which follows a Pareto distribution with pdf k/h^{k+1} and $k > 1$.[12]

In order to interview workers, a firm must pay a fixed search cost of f effective labor units, at which point they may hire from a distribution of worker types a_R. The firm hires on the basis of match quality, and consequently chooses a minimum threshold of match quality for each type they will retain, $\underline{h} = (\underline{h}_1, \ldots, \underline{h}_{\mathbb{S}})$.[13] Upon keeping a preferred set of workers, the firm chooses a continuous number N times to repeat this process until achieving their desired workforce. At the end of hiring, the amount of human capital produced by each type i is given by

$$H_i \equiv N \cdot a_{R,i} \underline{m}_i^T \int_{\underline{h}_i}^{\infty} h \cdot \left(k/h^{k+1}\right) dh. \tag{2.1}$$

From a firm's perspective, the threshold of worker match quality $\underline{h}$ is a means to choose an optimal level of H. However, as a firm lowers its quality threshold, it faces an increasing average cost of each type of human capital H_i . These increasing average costs induce the firm to maintain $\underline{h}_i \geq 1$ and to increase N to search harder for suitable workers.

The amount of L produced by the firm depends on the composition of a team through a tech-

[12] Clear extensions of the model would be to model individual worker characteristics or surplus sharing that gives rise to wage dispersion. However, these are beyond the scope of our stylized general equilibrium setting and data resolution. Instead, we will control for worker characteristics at the level of the firm in the empirics.

[13] This assumption is familiar from labor search models (see Helpman, Itskhoki, and Redding (2010)). Unlike Helpman, et al., here differences in hiring patterns are determined by local market conditions.

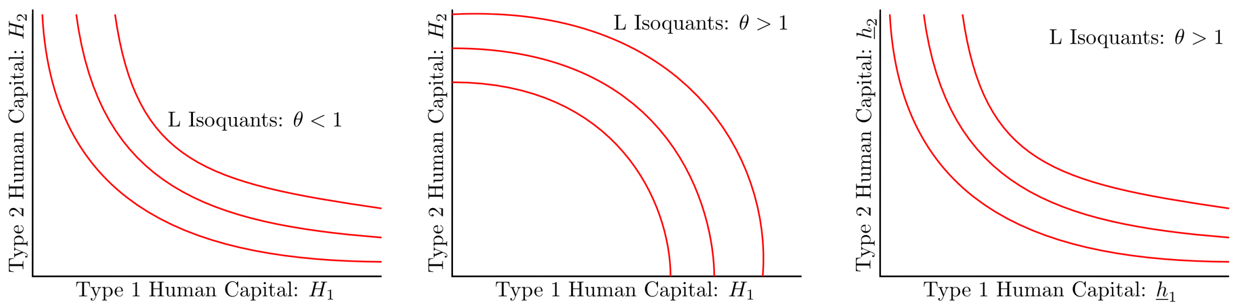
nological parameter θ^T in the following way:

$$L \equiv \left(H_1^{\theta^T} + H_2^{\theta^T} + \ldots + H_{\mathbb{S}}^{\theta^T}\right)^{1/\theta^T}. \tag{2.2}$$

Notice that in the case of $\theta^T = 1$, this specification collapses to a model where L is the total level of human capital $\sum H_i$. More generally, the Marginal Rate of Technical Substitution of type i for type i' is $(H_i/H_{i'})^{\theta^T-1}$. $\theta^T < 1$ implies worker types are complementary, so that the firm's ideal workforce tends to represent a mix of all types (Figure 2.1a). In contrast, for $\theta^T > 1$, firms are more dependent on singular sources of human capital as L becomes convex in the input of each single type (Figure 2.1b).[14] Below, we show that despite the convexity inherent in Figure 2.1b, once firms choose the quality of their workers through hiring standards $\underline{h}$, the labor isoquants resume their typical shapes as in Figure 2.1c, which allows for the possibility of $\theta^T > 1$ (which is often assumed away in many studies to ensure concavity of the firm's hiring problem.)

Figure 2.1: Human Capital Isoquants

(a) Supermodular Production in H (b) Submodular Production in H (c) Submodular Production in $\underline{h}$



Although the technology θ^T is the same for all firms in an industry, firms do not all face the same regional factor markets. Explicitly modeling these disparate markets emphasizes the role of regional heterogeneity in supplying human capital inputs to the firm in terms of both price and quality. This provides not only differences in productivity across regions by technology, but since industries differ in technology, local market conditions are more or less amenable to particular industries. We now detail the hiring process, introducing different markets and deriving firms' optimal hiring to best accommodate these differences.

2.2 Unit Labor Costs by Region and Technology

The total costs of hiring labor depend on the regional wage rates w_R, the availability of workers a_R, and the unit cost of labor in region R using technology T, labeled c_R^T. Since the total number

[14] See Morrow (2010) for a more detailed interpretation of super- and sub-modularity and implications.

of each type i hired is $Na_{R,i}/\underline{h}_i^k$, the total hiring bill is

$$\text{Total Hiring Costs :} \quad N\left[\sum_i w_{R,i}a_{R,i}/\underline{h}_i^k + fc_R^T\right]. \tag{2.3}$$

To produce effective labor, the firm faces a trade off between the quantity and quality of workers hired. For instance, the firm might hire a large number of workers and "cherry pick" the best matches by choosing high values for $\underline{h}$. Alternatively, the firm might save on interviewing costs f by choosing a low number of prospectives N and permissively low values for $\underline{h}$. The unit labor cost function (minimum of Equation (2.3) subject to $L = 1$) may be solved (Appendix G.4) as

$$\text{Unit Labor Costs :} \quad c_R^T = \left[\sum_{i \text{ hired}} \left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}/f\left(k-1\right)\right]^{\theta^T/\beta^T}\right]^{\left(\beta^T/\theta^T\right)/(1-k)}, \tag{2.4}$$

where

$$\beta^T \equiv \theta^T + k - k\theta^T. \tag{2.5}$$

The trade off between being more selective (high $\underline{h}$) and avoiding search costs (fc_R^T) is illustrated by the following Equation implied by the firm's first order conditions for cost minimization:

$$\sum_i a_{R,i}w_{R,i}\int_{\underline{h}_i}^{\infty}\left(h-\underline{h}_i\right)/\underline{h}_i \cdot \left(k/h^{k+1}\right)dh = fc_R^T. \tag{2.6}$$

The LHS of Equation (2.6) decreases in $\underline{h}$, so when a firm faces lower interviewing costs it can afford to be more selective by increasing $\underline{h}$. Conversely, in the presence of high interviewing costs, the firm optimally "lowers their standards" $\underline{h}$ to increase the size of their workforce without interviewing additional workers. The number of times a firm goes to hire workers, N, can be solved as $N = 1/fk$. Thus, N is decreasing in both hiring costs and k. Increases in k imply lower expected match quality, so that repeatedly searching for new workers has lower returns.

2.3 Optimal Local Hiring Patterns

The above reasoning shows the relationship between technology and the optimal choice of worker types. It is intuitive that if the right tail of the match quality distribution is sufficiently thick, there are excellent matches for each type of worker, so all types are hired.[15] Since match quality follows a Pareto distribution with shape parameter k, expected match quality is $k/(k-1)$. As k

[15]This is important, not only for the analytical convenience of avoiding complete specialization in the hiring of worker types, but also because we find that each region-industry combination hires all types of workers in the data.

approaches one, match quality increases, so for k sufficiently close to one, all worker types are hired. A sufficient condition for a firm to optimally hire every type of worker, stated as Proposition 1, is that β^T of (2.5) is positive.[16] This induces the isoquants depicted in Figure 2.1c, which illustrates a more standard trade off between different types of workers, so long as the coordinates are transformed to the space of hiring standards $\underline{h}$.

Proposition 1. *If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers.*

Proof. See Appendix. □

Thus, for $\beta^T > 0$, all worker types are hired. The optimal share of workers of type i hired by firm j under technology T in region R, labeled $s^T_{R,ij}$, is:[17]

$$s^T_{R,ij} = a_{R,i}^{\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} \left(\tilde{c}_R^T\right)^{(k-1)\theta^T/\beta^T} \left(f\left(k-1\right)\right)^{-\theta^T/\beta^T}. \tag{2.7}$$

where $\tilde{c}_R^T$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$. Notice that in (2.7) , unlike most production models, the factor prices w_R are not sufficient to determine the factor shares a firm will buy. The availability of workers a_R is crucial in determining shares hired because costly search makes firms sensitive to the local supply of each worker type.[18]

2.4 Unit Costs: The Role of Substitution

In order to model substitution into non-labor inputs conditional on local labor costs, we assume the production technology of each industry T assumes a Cobb-Douglas form:

$$\text{Output for a firm in Industry } T: \quad M^{\alpha_M^T} K^{\alpha_K^T} L^{\alpha_L^T}, \text{ where } \alpha_M^T + \alpha_K^T + \alpha_L^T = 1. \tag{2.8}$$

Industry specific capital is available to firms at rental rate r_K^T and similarly, materials are available at price r_M^T. However, regional characteristics may augment or reduce the effectiveness of capital and materials in a region by frictions κ_R and μ_R, so that the effective rental rate of capital in region R is $\kappa_R r_K^T$ and the effective price of materials is $\mu_R r_M^T$.[19]

Equation (2.4) summarizes the cost of one unit of labor L in terms of the Pareto shape parameter k, the technology θ^T and regional characteristics a_R and w_R. It is then straightforward to derive

[16] This clearly holds for $\theta^T \leq 1$, and for $\theta^T > 1$, the condition is equivalent to $k < \theta^T / \left(\theta^T - 1\right)$.

[17] See Supplemental Appendix.

[18] One potentially important extension beyond the scope of our data is firm transition dynamics with existing workforces who take time to adapt to changes in local labor markets.

[19] One view of this assumption is that it allows for a static realization of regional dynamic forces that influence factor efficiency that are beyond the scope of this paper, e.g. Cingano and Schivardi (2004). Another is that it captures differences in local factor market development (e.g. for credit as in Guiso, Pistaferri, and Schivardi, 2013).

total unit costs from (2.4) and (2.8) as

$$\text{Total Unit Costs :} \quad u_R^T = \left(\kappa_R r_K^T/\alpha_K^T\right)^{\alpha_K^T} \left(\mu_R r_M^T/\alpha_M^T\right)^{\alpha_M^T} \left(c_R^T/\alpha_L^T\right)^{\alpha_L^T}, \tag{2.9}$$

where u_R^T represents the regional component of unit costs for industry T in region R. Within an industry, productivity then varies across regions as in the following example: assume Firm 1 in region R and Firm 2 in region R' have the same total expenditure on inputs, E. By definition, Firm 1's output, Y_1, is E/u_R^T while Firm 2's output Y_2 is $E/u_{R'}^T$. Therefore relative output is

$$Y_1/Y_2 = u_{R'}^T/u_R^T = \left(\kappa_{R'}/\kappa_R\right)^{\alpha_K^T} \left(\mu_{R'}/\mu_R\right)^{\alpha_M^T} \left(c_{R'}^T/c_R^T\right)^{\alpha_L^T}.$$

Industry differences in productivity therefore depend on 1) regional labor costs and quality and 2) the intensity of factors in production. Estimating both quantifies regional productivity differences. However, we first resolve factor prices and firm location in general equilibrium.

3 Firm Production under Monopolistic Competition

This section combines the insights into firm behavior just developed into a general equilibrium model to understand the implications of regional factor markets for welfare and firm location. Firms, who are ex ante identical, choose among regions to locate. Key to a firm's location decision are the expected profits of entry. These profits depend on 1) the regional distribution of worker types and wages, 2) capital and material quality and 3) the competition present from other firms who enter the region. We characterize production and location choices conditional on local factor markets. Most strikingly, lower regional production costs attract more firms for any given technology, which determines the intensity of economic activity.

Furthermore, we show an equilibrium wage vector exists which supports these choices by firms for any distribution of labor endowments (e.g. as would be implied by assuming nominal or real wage equalization across regions). Thus, endowment distributions as implied by both complete or incomplete labor mobility are consistent with this framework. Rather than use a macro level model which determines worker location *a priori*, we will use micro level population census data to observe the actual composition of labor markets.[20] Our goal is to understand how firms optimally respond to local factor markets as they are, not to predict where workers choose to locate.

[20] There are many forces at work in determining the composition of local labor markets in China. In this respect, the literature is even unresolved as to what extent Chinese labor markets reflect an agriculturally transitioning 'dual economy' (Zhang, Yang, and Wang, 2011) or if models best suited to advanced industrial economies are more appropriate. Since China has undergone sweeping changes within the last generation, we remain agnostic and rely on the data.

3.1 Firms and Consumers

Each region R is endowed with a population $\mathbb{P}_R$. Firms may enter any region R by paying a sunk entry cost of F_e output units, which costs $u_R^T F_e$. Firms then receive a random marginal cost draw $\eta_j \sim G$ and face a fixed production cost of f_e output units, which costs $u_R^T f_e$.[21] Each firm j produces a distinct variety which is freely traded, produces a quantity Q_{Rj}^T, and in equilibrium a mass of firms $\mathbb{M}_R^T$ enter. Entrants who can make variable profits above fixed costs produce, namely those with cost draws below some level $\overline{\eta}_R^T$. $\mathbb{M}_R^T$ and $\overline{\eta}_R^T$ together determine the set of varieties available to consumers.

Consumer preferences over varieties take the Dixit-Stiglitz form

$$U_R^T \equiv \mathbb{M}_R^T \int_0^{\overline{\eta}_R^T} \left(Q_{Rj}^T\right)^\rho dG(j)$$

in each region and industry, with total utility $\sum_{T,R} \sigma_R^T \ln U_R^T$, where σ_R^T are relative weights put on final goods normalized so that $\sum_{T,R} \sigma_R^T = 1$. As shown in the Appendix, each σ_R^T is the share of income spent on goods from each region and technology pair (R,T).[22]

Firms are the sole sellers of their variety, and thus are monopolists who provide their variety at a price P_{Rj}^T. Consumers, in turn, face these prices, and a particular consumer with income I has the following demand curve for each variety:

$$Q_{Rj}^T = I \cdot \left(P_{Rj}^T U_R^T / \sigma_R^T\right)^{\frac{1}{\rho-1}} / \sum_{t,r} \left(\sigma_r^t\right)^{\frac{1}{\rho-1}} \mathbb{M}_r^t \int_0^{\overline{\eta}_r^t} \left(\left(P_{r,z}^t\right)^\rho U_r^t\right)^{\frac{1}{\rho-1}} dG(z). \tag{3.1}$$

From Equation (3.1), clearly aggregate demand for variety j corresponds to that of a representative consumer with income equal to aggregate income, $\mathbb{I}$.[23]

After paying an entry cost, firms know their cost draw, which paired with regional input markets determine their total unit cost u_R^T. Firms maximize profits by choosing an optimal price $P_{Rj}^T = u_R^T \eta_j / \rho$, resulting in a markup of $1/\rho$ over costs. Firms who cannot make a positive profit do not produce to avoid paying the fixed cost of production. Since profits decrease in costs, there is a unique cutoff cost draw $\overline{\eta}_R^T$ which implies zero profits, while firms with $\eta_j < \overline{\eta}_R^T$ produce.[24] As there are no barriers to entry besides the sunk entry cost F_e, firms enter in every region until

[21] This follows Melitz (2003). $G(\eta)$ is assumed to be absolutely continuous with $\mathrm{E}\left[\eta^{\rho/(\rho-1)}\right]$ finite.

[22] Note that since the demand for goods from each (R,T) pair enter preferences multiplicatively, complete specialization cannot occur which considerably simplifies the analysis.

[23] Since labor is supplied inelastically, necessarily $\mathbb{I} = \sum_R \sum_i \underbrace{w_{R,i} a_{R,i} \mathbb{P}_R}_{\text{Total Wages of Type i in R}} + \sum_R \sum_T \underbrace{\tau_R^M r_M^T M^T + \tau_R^K r_K^T K^T}_{\text{Non-labor Income}}$.

[24] The Appendix shows the cutoff cost $\overline{\eta}_R^T$ depends only on f_e, F_e, and G, and so does not vary by region or industry.

expected profits are zero. This yields the

$$\text{Spatial Zero Profit Condition}: \quad \int_0^{\overline{\eta}_R^T} \underbrace{\left(P_{Rj}^T - u_R^T \eta_j\right) Q_{Rj}^T - u_R^T f_e}_{\text{Profits for firm } j \text{ in } R,T} dG(j) = u_R^T F_e \quad \text{for all } R, T.$$

3.2 Local Factor Markets and Welfare

Finally, differences in regional factor markets influence consumer welfare. As shown in the appendix, the equilibrium welfare of an economy with income $\mathbb{I}$ and Industry-Region unit costs is given by (here Constant depends only on f_e, F_e, G, ρ and σ_R^T, see Appendix G.6):

$$\text{Welfare} = \text{Constant} + \ln \mathbb{I} - \ln \sum_{T,R} \sigma_R^T \ln u_R^T. \tag{3.2}$$

From Equation (3.2), if unit costs were to change to $\left\{v_R^T\right\}$ while holding aggregate income constant, after allowing firms to adjust location and production decisions, the percentage change in real income under from old to new unit costs would be

$$\text{Percentage Change in Real Income} = \prod_{T,R} \left(u_R^T / v_R^T\right)^{\sigma_R^T} - 1. \tag{3.3}$$

Having determined behavior in the product market, we now examine input markets.

3.3 Regional Factor Market Clearing

The remaining equilibrium conditions are that input prices guarantee firm input demand exhausts materials, capital stocks, and each regional pool of workers. We assume industry specific stocks of capital (K^T) and materials (M^T) are available. To fix expenditure, we assume each budget share σ_R^T is proportional to $\mathbb{P}_R$, so that $\sigma_R^T = \sigma^T \mathbb{P}_R$ for some σ^T.[25] Since production is Cobb-Douglas, the share of total costs (equal to $\mathbb{I}$) which go to each factor is the factor output elasticity. Therefore full resource utilization of materials and capital requires the effective capital (K_R^T) and materials (M_R^T) used in each region to satisfy

$$M^T = \sum_R \mu_R M_R^T = \alpha_M^T \sigma^T \mathbb{I}\mathbb{P} / r_M^T, \qquad K^T = \sum_R \kappa_R K_R^T = \alpha_K^T \sigma^T \mathbb{I}\mathbb{P} / r_K^T, \tag{3.4}$$

where $\mathbb{P} \equiv \sum_R \mathbb{P}_R$ is the total population. These equations capture the allocation of technology specific resources across regions.

[25]This assumption implies that any two regions with identical skill distributions have the same wage schedule.

In contrast, effective labor of L_R^T is produced by each technology in each region. Since the wage bill $L_R^T c_R^T$ must receive a share α_L^T of total revenues,

$$\text{Aggregate Labor Demand}: \quad L_R^T = \alpha_L^T \sigma^T \mathbb{I}\mathbb{P}_R / c_R^T. \tag{3.5}$$

Embedded in each L_R^T is the set of workers hired by firms attendant to regional market conditions. The total demand for employees of each type in region R implied by Equation (2.7) must equal the supply of $a_{R,i}\mathbb{P}_R$. Wages are therefore determined by

$$a_{R,i} w_{R,i} = \sum_T \underbrace{\sigma^T}_{\text{Industry Share Per Capita}} \cdot \underbrace{\alpha_L^T}_{\text{Labor Share}} \cdot \underbrace{H_{R,i}^{\theta^T} / \Sigma_z H_{R,z}^{\theta^T}}_{\text{Type Share}} \cdot \mathbb{I} \quad \text{for all } R, i. \tag{3.6}$$

Equation (3.6) shows that type i's contribution to mean wages, $a_{R,i} w_{R,i}$, is the sum over income spent an industry, times labor's share, times the wages attributable to each type.[26]

Solving Equation (3.6) requires finding a wage for each worker type in each region that fully employs all workers. We do so in the Appendix, leading to

Proposition 2. *An equilibrium wage vector exists which clears each regional labor market.*

3.4 Regional Specialization of Firms

Differences in input costs will influence the relative concentration of firms across regions through entry. Since regions vary in population size, the relevant metric is the mass of firms per capita. The impact of different regional costs on the mass of firms can be clearly seen by fixing an industry T and considering a region R versus a region R', as given by Proposition 3.

Proposition 3. *Regions with lower factor costs have more firms per capita. In particular, if $\mathbb{F}_R^T$ denotes the mass of firms per capita in region R, industry T then*

$$\ln\left(\mathbb{F}_R^T / \mathbb{F}_{R'}^T\right) = \alpha_K^T \ln\left(\kappa_{R'} / \kappa_R\right) + \alpha_M^T \ln\left(\mu_{R'} / \mu_R\right) + \alpha_L^T \ln\left(c_{R'}^T / c_R^T\right). \tag{3.7}$$

Proof. See Appendix. □

Equation (3.7) shows that areas with lower unit labor costs, capital costs or material costs have more firms per capita. Note that these differences in firm density are not driven simply by factor prices. Even if wages and frictions were identical across regions, the suitability of available workers a_R can cause regional specialization through differences in unit labor costs. Additionally, the larger the share of a factor in production, the more important are differences between regions.

[26] The equilibrium type share is $H_{R,i}^{\theta^T} / \Sigma_z H_{R,z}^{\theta^T} = \left(a_{R,i} \left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}\right)^{\theta^T/\beta^T} / \Sigma_j \left(a_{R,j} \left(\underline{m}_j^T\right)^k w_{R,j}^{1-k}\right)^{\theta^T/\beta^T}$.

The next section lays out a strategy to structurally estimate model parameters.

4 Estimation Strategy

This section lays out an estimator for the structural model parameters above. The estimator involves two stages, with a simple intervening computation. The first stage determines regional quality and firm labor demand, and unlike many approaches, is based on the firm-level shares of workers hired across regions. The second stage equation uses regional unit labor costs from the first stage to estimate the production function. Feasibility is illustrated by simulating a data set consistent with the model above and recovering model primitives accurately with the estimator.

4.1 First Stage Estimation

As our estimation is performed for each industry T separately, here we will suppress industry superscripts for brevity.

4.1.1 Estimating Firm Workforce Composition

Equation (2.7) determines the share of each type of workers hired in each region R and industry T. Taking logs and allowing for errors ε_{ij} across firms j and types i implies

$$\ln s_{R,ij} = -(k/\beta)\ln w_{R,i} + (\theta/\beta)\ln a_{R,i} + (\theta k/\beta)\ln \underline{m}_i + \text{Fixed Effect}_R + \varepsilon_{ij}, \tag{4.1}$$

To estimate this equation we use a combination of type and region fixed effects.[27] To further explain how regional variation identifies the model we discuss equilibrium hiring predicted by Equation (4.1) in Appendix G.2.

In order to control for firm characteristics which might influence hiring patterns across worker types, $\underline{m}_i$ is allowed to vary with firm observables labeled Controls_j:

$$\underline{m}_{ij} \equiv \underline{m}_i \cdot \exp\left(\text{Controls}_j \gamma_i\right), \tag{4.2}$$

where γ_i is a type-industry specific control for the value of each worker type in an industry. The inclusion of Controls_j allows unit costs to vary by firm within a region. We will use such worker type specific controls to capture the effects of economic geography (e.g. deeper urban labor markets and skill agglomeration) and firm organization (e.g. foreign ownership). Finally, the linear

[27] This estimation strategy identifies relative worker type contributions, e.g. type and region fixed effects omitting the highest type correspond to estimates of $(\theta/\beta)k\ln \underline{m}_i/\underline{m}_{\mathbb{S}}$. This strategy does not identify the labor required to find workers (f), and consequently in subsequent estimation steps f will be differenced out by the industry average.

form of Equation (4.1) allows many well understood estimation techniques to be applied to the model, such as instrumental variable approaches.

4.1.2 Estimating Regional Frictions

Regional capital and material quality can be estimated using each firm j's input expenditure ratios of capital to wages ($K_{R,j}/W_{R,j}$) and materials to wages ($M_{R,j}/W_{R,j}$), because at the region level, these ratios deviate from the industry average. In particular, allowing for errors $\zeta_{j,K}$ and $\zeta_{j,M}$, the Cobb-Douglas production technology of (2.8) implies

$$\ln K_{R,j}/W_{R,j} = \ln \alpha_K/\alpha_L r_K - \ln \kappa_R + \zeta_{j,K}, \quad \ln M_{R,j}/W_{R,j} = \ln \alpha_M/\alpha_L r_M - \ln \mu_R + \zeta_{j,M}. \tag{4.3}$$

4.1.3 The Role of Model Assumptions in Estimation

Implicit in this estimation strategy is the assumption that firms take local factor market conditions as exogenous to their own behavior. In particular, we have assumed firms do not have monopsony power over their local factor market (e.g. Manning (2011)), and accordingly we restrict our analysis to regions with a minimum of five employers.

Since we are explaining firm hiring behavior in response to exogenous local market conditions, one endogeniety concern might be that regional factors simultaneously shift the supply or wages of manufacturing workers and individual firm demand across worker types. Accordingly, below we implement an instrumental variables strategy to address this potential source of endogeniety and assess the robustness of the estimates.

Finally, the estimates of unit labor costs and regional frictions for capital and materials are completely distinct and do not rely on estimates of each other. However, all of them together influence the estimation of substitution between these three inputs, which we now detail.

4.2 Second Stage Estimation

The first stage estimator just laid out estimates θ, k, $\underline{m}_i/\underline{m}_{\mathbb{S}}$, and γ_i. Therefore can estimate intraindustry differences in unit labor cost functions, $\Delta \ln c_R \equiv \mathrm{E}\left[\ln c_{Rj}|R,T,\text{Controls}_j\right] - \mathrm{E}\left[\ln c_{Rj}|T\right]$. From above, revenues $P_{Rj}Q_{Rj}$ for a firm j satisfy

$$\ln P_{Rj}Q_{Rj} = \alpha_M \ln M_j/\mu_R + \alpha_K \ln K_j/\kappa_R + \alpha_L \ln L_j - \ln \rho - \ln \eta_j. \tag{4.4}$$

As firm expenditure on labor $L \cdot c_{Rj}$ equals the share α_L of revenues $P_{Rj}Q_{Rj}$, we have $L_j c_{Rj} = \alpha_L P_{Rj} Q_{Rj}$ and taking differences with the industry mean gives

$$\Delta \ln L_j = \Delta \ln P_{Rj} Q_{Rj} - \Delta \ln c_{Rj}. \tag{4.5}$$

Taking differences of Equation (4.4) with the industry mean and rearranging using (4.5) yields

$$\Delta \ln P_{Rj} Q_{Rj} = \frac{\alpha_M}{1-\alpha_L} \Delta \ln \frac{M_j}{\mu_R} + \frac{\alpha_K}{1-\alpha_L} \Delta \ln \frac{K_j}{\kappa_R} - \frac{\alpha_L}{1-\alpha_L} \Delta \ln c_{Rj} - \frac{1}{1-\alpha_L} \Delta \ln \eta_j. \tag{4.6}$$

In the Appendix, we illustrate the estimator by simulating the production model above and apply these steps. In the simulation, the two stage estimator explains 97% of the variation in firm output, suggesting that the ease of implementation comes at only a small efficiency cost. Since the equations implied by the model are linear, well known methods to accommodate such features as heteroskedasticity can be easily introduced.

The entire estimation procedure is now briefly recapped.

4.3 Estimation Procedure Summary

The data required to estimate the impact of the local labor on firm composition is:

1. The shares of worker types within firms.

2. The average wages and workforce shares of each worker type in a firm's locality.

These are used to estimate Equation (4.1) by industry, using type and region fixed effects.

Optionally, the regional quality of capital and materials may be estimated using input expenditure ratios and industry fixed effects as in Equation (4.3). The remaining procedure is as follows:

1. Recover $\widehat{\theta}$, $\widehat{k}$, $\widehat{\underline{m}_i/\underline{m}_{\mathbb{S}}}$ and $\widehat{\gamma}_i$ (optionally $\widehat{\kappa_R}$, $\widehat{\mu_R}$) and bootstrap standard errors.

2. Calculate $\widehat{\Delta \ln c_{Rj}}$ from Equation (2.4) using regional data and estimated parameters.

3. Estimate Equation (4.6) using firm production data, $\widehat{\Delta \ln c_{Rj}}$, $\widehat{\kappa_R}$ and $\widehat{\mu_R}$. Errors can be modeled through FGLS, and by construction should allow the error variance to vary by region.

Having laid out both a model detailing the interaction of firm technologies with local market conditions and specifying an estimation strategy, we now apply the method to China. The next section discusses these data in detail while the sequel presents results.

5 Data

Firm data come from the 2004 Survey of Industrial Firms conducted by the Chinese National Bureau of Statistics, which includes all state owned enterprises and private enterprises with sales over 5 million RMB. The data include firm ownership, location, industry, employees by education level, profit and cash flow statements. Firm capital stock is reported fixed capital, less reported depreciation while materials are measured by value. For summary statistics, see Appendix H.1. From the Survey, a sample was constructed of manufacturing firms who report positive net fixed assets, material inputs, output, value added and wages.[28][29] The final sample includes 127,082 firms in 284 prefectures and 16 industries at the two digit Chinese Standard Industrial Classification level.

Regional wage distributions are calculated from the 0.5% sample of the 2005 China Population Census. The census contains the education level by prefecture of residence, occupation, industry code, monthly income and weekly hours of work. We restrict the sample to employees age 15 to 65 who report positive wages and hours of work. The regional wage distribution is recovered from the average annual income of employees by education using census data.[30]

GIS data from the China Data Center at the University of Michigan locates firms at the county and prefecture level. Port locations are provided by GIS data and supplemented by data from the World Port Index. These data provide controls for urban status, distance to port, highway density and distance to cities.

Finally, welfare calculations rely on household consumption shares for each industry are aggregated from the three digit level from the 2002 Input-Output Table of China, as constructed by the Department of National Economy Accounting, State Statistical Bureau.

Figure 5.1a illustrates the prefectures of China, which we define as regions from the perspective of the model above. Prefectures are similar in population size to a US commuting zone, as used by Autor, Dorn, and Hanson (2013) and computed by Tolbert and Sizer (1996). Prefectures illustrated by a darker shade in the Figure operate under substantially different government policies and objectives. These regions typically have large minority populations or historically distinct conditions, with the majority declared as autonomous regions, and have idiosyncratic regulations, development, and educational policies. We exclude the five Autonomous Provinces and one predominantly minority Province (Qinghai) which has a very low density of population and economic

[28]The results are robust to exclusion of firms with fewer than 8 employees which operate in a different legal regime.

[29]The welfare counterfactuals for industries with $\beta < 0$ are theoretically problematic so we exclude them.

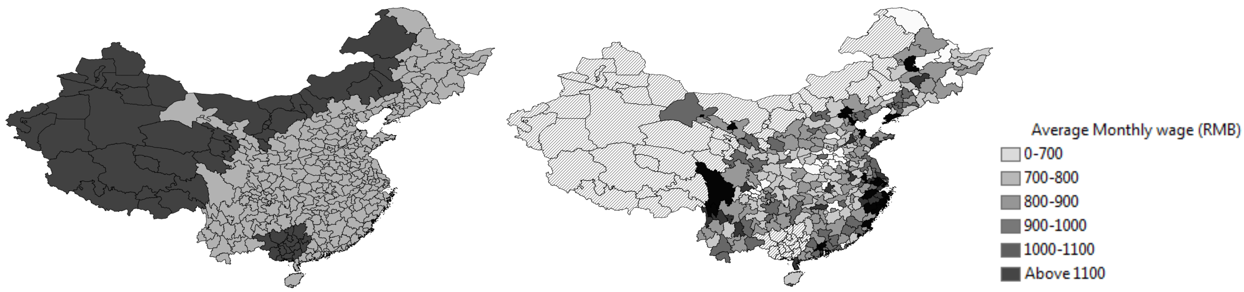
[30]While firm data is from 2004 and census data is from 2005, the limited evidence on firm skill mix is that it is remarkably stable over time: Ilmakunnas and Ilmakunnas (2011) find the standard deviation of plant-level education years is very stable from 1995-2004 in Finland, and Parrotta, Pozzoli, and Pytlikova (2011) find that a firm-level education diversity index was roughly constant over a decade in Denmark.

activity.[31] What remains are the lighter shaded regions of Figure 5.1a, preserving 284 prefectures displaying distinct labor market conditions.

Figure 5.1: Chinese Prefectures

(a) Chinese Prefectures

(b) Average Monthly Income of Employees (2005)



5.1 Worker Types

Workers are defined as people between ages 15 and 65 who work outside the agricultural sector and are not employers, self-employed, or in a family business. This characterization includes migrants. The definition of distinct, imperfectly substitutable worker types is based primarily on formal schooling attained. Census data from 2005 shows that the average years of schooling for workers in China ranges from 8.5 to 11.8 years across provinces, with sparse postgraduate education. The most common level of formal education is at the Junior High School level or below. Reflecting substantial wage differences by gender within that group, we define Type 1 workers as Junior High School or Below: Female and Type 2 workers as Junior High School or Below: Male.[32] Completion of Senior High School defines Type 3 and completion of Junior College or Higher Education defines Type 4.

5.2 Regional Variation

Key to the analysis is regional variation in skill distribution and wages. Here we briefly discuss both, with further details in Appendix H. While this paper explains individual firms' responses to existing labor market conditions rather than providing a theory of worker location, it is clear that the recent history of China has exhibited massive internal migration (Chan, 2013).[33] Monthly incomes vary substantially across China as illustrated in Figure 5.1b. This is due to both the composition of

[31] See the Information Office of the State Council of the People's Republic of China document cited.

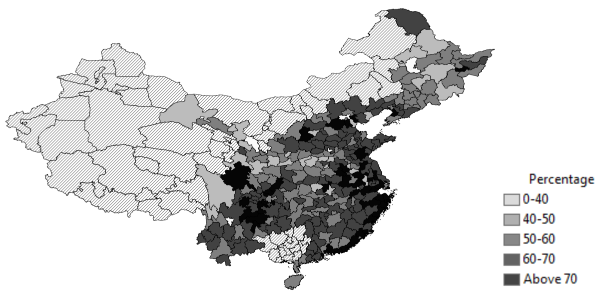
[32] Differentiation of gender for low skill labor is especially important in developing countries as a variety of influences result in imperfect substitutability across gender. Bernhofen and Brown (2011) distinguish between skilled male labor, unskilled male labour and female labour and find that the factor prices across these types differ substantially.

[33] In 2005, the median share of within prefecture migration is 77 percent, dominating across prefecture migration.

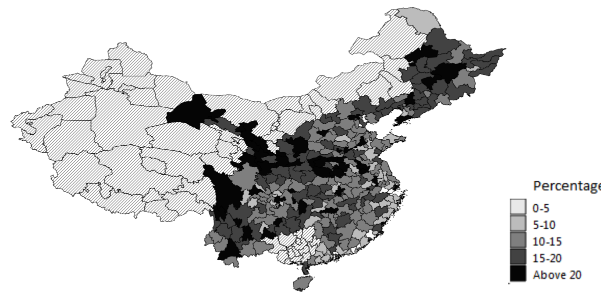
skills (proxied by education) across regions and the rates paid to these skills. Figure 5.2 contrasts educational distributions of the labor force. Figure 5.2(a) shows those with a Junior High School education (the mandated level in China), while Figure 5.2(b) displays those with a Junior College or higher level of attainment.

Figure 5.2: Low and High Educational Attainment Across China (2005)

(a) % Labor Force with $\leq$ Junior High School



(b) % Labor Force with $\geq$ Junior College



The differing composition of input markets across China in 2004-2005 stem from many factors, including the dynamic nature of China's rapidly growing economy, targeted economic policies and geographic agglomeration of industries across China.[34] Faber (2014) finds that expansion of China's National Trunk Highway System displaced economic activity from counties peripheral to the System. Similarly, Baum-Snow, Brandt, Henderson, Turner, and Zhang (2017) show that mass transit systems in China have increased the population density in city centers, while radial highways around cities have dispersed population and industrial activity. An overview of Chinese economic policies is provided by Defever and Riano (2017), who quantify their impact on firms.

Of particular interest for labor markets are substantial variation in wages and the attendant migration this induces. The quantitative extent to which labor market migration has been stymied by the *hukou* system of internal passports is not well studied, although its impact has likely lessened since 2000.[35] Since little is known about the impact of illegal immigration on firm behavior (see Brown, Hotchkiss, and Quispe-Agnoli (2013) for a notable exception), and as the ease of obtaining a legal hukou is not independent of education,[36] we control for the regional share of non-agricultural hukou held by each type of worker without any *a priori* expectation of sign. Given that rural to urban migration typifies the pattern of structural transformation underway, we

[34] We consider regional price variation at a fixed point in time. Reallocation occurs (Ge and Yang, 2014) and is important in explaining dynamics (e.g. Borjas (2003)), but dynamics are outside the scope of this paper.

[35] The Hukou system and its reform in the late 1990s are well explained in Chan and Buckingham (2008). The persistence of such a stratified system has engendered deep set social attitudes which likely affect economic interactions between Hukou groups, see Afridi, Li, and Ren (2012).

[36] High income and highly educated workers can more easily move among urban regions as local governments are likely to approve their migration applications (Chan, Liu, and Yang, 1999).

control for rural and urban effects for each type of worker below. While modeling dynamic worker considerations is beyond the scope of this paper, presumably the dynamic forces that impact the manufacturing labor force would similarly impact the service sector labor force, and accordingly we re-estimate the structural parameters instrumenting manufacturing labor market conditions with service sector labor market conditions as reported by the Population Census sample.

Having discussed the data, we now apply the estimation procedure developed above.

6 Estimation Results

This section reports estimation results, then turns to a discussion of the quantitative labor cost and productivity differences accounted for by local market conditions in China. The section continues by comparing the ability of the model to explain productivity differences with this unit cost based method with one approach common in the literature, which does not account for regional factor markets and models labor types as input stocks. We then quantify the importance of the estimated productivity differences for welfare by using the general equilibrium model to consider a hypothetical Chinese economy in which the distribution of workers and wages across regions is equalized. Finally, we test the firm location implications of the model, finding support that economic activity locates where estimated unit labor costs are lower.

6.1 Estimates of Market Conditions and Production Technologies

The full first stage regression results for several manufacturing industries in China are presented in Tables A.3 and A.4 of Appendix C. A representative set of estimates for the General Machines industry are presented in Table 1. The first box in Table 1, labeled Primary Variables, are consistent with the model: increases in the local wages for a type decrease firm demand for that type, while increases in the availability of a type increase firm demand.[37] Though values for the coefficients $\left(\theta^T/\beta^T\right)\ln \underline{m}_i^T/\underline{m}_4^T$ are not specified by the model, their estimated values do increase in type in Table 1, which is consonant with formal education increasing worker output.

The remaining two boxes include regional controls from the Census and firm level controls from the manufacturing survey. The regional controls are by prefecture, and include the percentage of each type with a non-agricultural Hukou. The firm level controls include the share of foreign equity, whether the firm is in an urban area, and the age of the firm. Most interestingly, firms in urban areas or with higher shares of foreign equity tend to have increasingly higher demand for

[37] This second result is in line with recent findings on firm and industry responses to changes in labor supply of Gonzalez and Ortega (2011) and Dustmann and Glitz (2015).

higher skilled workers, as evidenced by the increasing pattern of coefficients across worker types.[38]

Table 1: First Stage Results: General Machines

Primary Variables	$\ln(\%\text{ Hired})$	Firm Controls	
$\ln(w_{R,i})$	-2.687***	$\underline{m}_1 *$ Urban Dummy	-1.384***
$\ln(a_{R,i})$	1.794***	$\underline{m}_2 *$ Urban Dummy	-0.980***
$\underline{m}_1$ ($\leq$Junior HS: Female)	-10.170***	$\underline{m}_3 *$ Urban Dummy	0.427***
$\underline{m}_2$ ($\leq$Junior HS: Male)	-6.171***	$\underline{m}_4 *$ Urban Dummy	2.336***
$\underline{m}_3$ (Senior High School)	-3.180***	$\underline{m}_1 *\%$ Foreign Equity	-2.448***
		$\underline{m}_2 *\%$ Foreign Equity	-1.864***
		$\underline{m}_3 *\%$ Foreign Equity	0.311***
Regional Controls		$\underline{m}_4 *\%$ Foreign Equity	3.847***
$\underline{m}_1 *\%$ Non-Ag Hukou	-5.957***	$\underline{m}_1 * \ln(\text{Firm Age})$	0.934***
$\underline{m}_2 *\%$ Non-Ag Hukou	-3.072***	$\underline{m}_2 * \ln(\text{Firm Age})$	0.403***
$\underline{m}_3 *\%$ Non-Ag Hukou	-3.218***	$\underline{m}_3 * \ln(\text{Firm Age})$	0.143***
$\underline{m}_4 *\%$ Non-Ag Hukou	-7.026***	$\underline{m}_4 * \ln(\text{Firm Age})$	0.351***
Observations: 62,908. R^2 : 0.139		Includes Regional Fixed Effects	
Significance: *** p<.01, ** p<.05, * p<.1.			

Inclusion of controls for average worker age, which control for accumulated skill or vintage human capital, do not appreciably alter the results. Other controls which did not appreciably alter the results include state ownership[39], distance to port, firm size and the percentage of migrants in a region.

6.1.1 Explanatory Importance of Local Worker Availability versus Wages

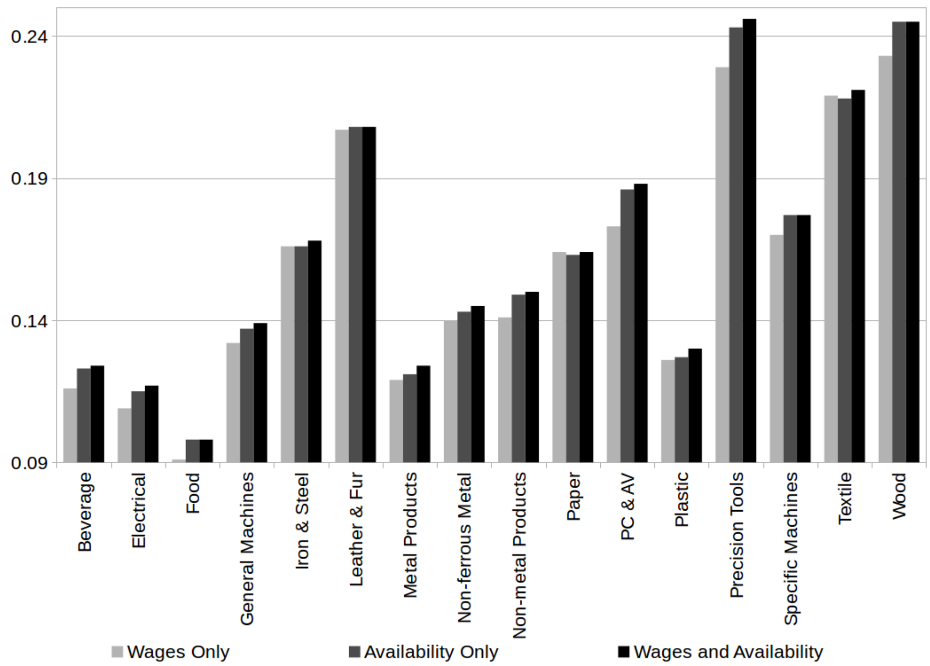
One innovation of the model and empirical strategy is to estimate and quantify the role of local worker availability in firm hiring decisions. While this is novel, its empirical relevance is supported by both the significance of the coefficients on worker availability (Tables A.3 and A.4), but also by the higher explanatory value of worker availability. This is demonstrated in Figure 6.1, which displays the R^2 of regressions by industry using the specification of Table 1 in black, and the corresponding R^2 for the same specification omitting availability (light grey) or wages (dark grey). In almost every industry, worker availability explains more firm workforce variation than wages.[40]

[38] The latter of these two patterns is supported by estimates of the skill composition in Swedish firms by Carl Davidson, Fredrik Heyman, Steven Matusz, Fredrik Sjoholm, and Susan Zhu (2013).

[39] The industries with the highest shares of state ownership, Printing and Transport, were censored over concerns regarding hiring incentives and geographic location. Both industries are relatively capital intensive, so that labor market effects are of secondary importance.

[40] Bootstrapping the sample shows we can reject the hypothesis that the R^2 of the wage regressions is higher than the R^2 of the availability regressions at the 95% confidence level in 13 of 16 industries.

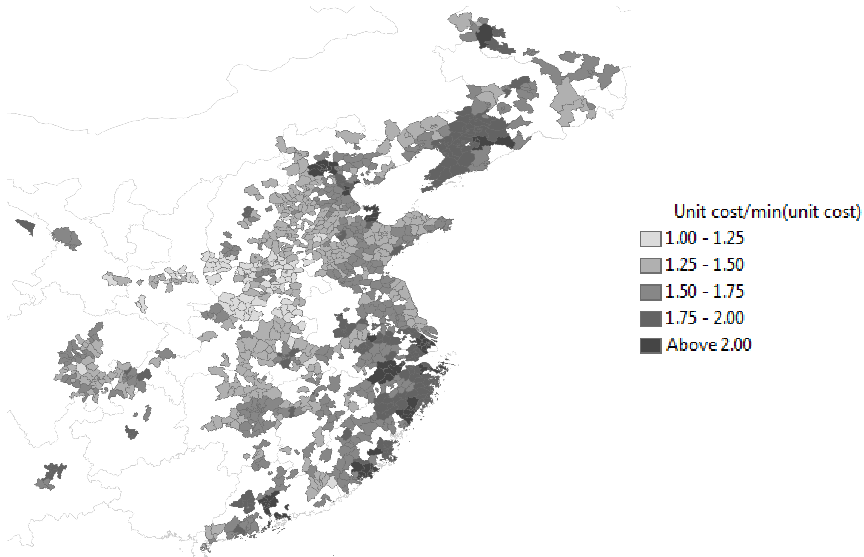
Figure 6.1: Explanatory Power of Worker Wages versus Availability by R^2



6.1.2 Differences in Production Costs by Region

These first stage estimates are interesting in themselves, as the model then implies the unit cost function for labor by region. The dispersion of estimated unit labor costs in the General Machines industry are depicted in Figure 6.2. As General Machines is an industry with $\theta^T > 1$, low cost areas (light grey) represent areas with a combination of not only low wages, but deep pools of similar types of workers.

Figure 6.2: Geographic Dispersion of Unit Labor Costs: General Machines



Other features of regional factor markets might influence the relative quality of capital and materials to labor, such as the depth of input/output markets, infrastructure or agglomerative forces. To control for these features, we use Equation (4.3) to estimate regional capital and material quality using the distance from the center of each firm's county to the nearest large city, arriving at

$$\widehat{\ln \kappa_R} = \underset{(.096)}{.315} \cdot \text{Distance to City (per 100 km)} + \text{Industry Fixed Effect},$$

$$\widehat{\ln \mu_R} = \underset{(.123)}{.236} \cdot \text{Distance to City (per 100 km)} + \text{Industry Fixed Effect}.$$

The model primitives of the two stage estimation procedure across industries are summarized in Table 2. Standard errors are calculated using a bootstrap stratified on industry and region, since these estimates rely on the first stage estimates of structural model parameters. Table 2 displays the estimated model primitives, showing a range of significantly different technologies θ^T and match quality distributions through k. Table 2 also shows the second stage estimation results, where the regional unit labor costs are calculated using regional data and the first stage estimates.[41]

[41] These second estimates include controls for the percentage of female and white collar workers, percentage of state and foreign equity, share of revenues exported and the logarithm of the age of the firm.

Table 2: Structural Model Estimates

Industry	k	θ	α_L	α_K	α_M
Beverage	2.12 (.38)	1.24 (.08)	.18 (.04)	.13 (.01)	.62 (.04)
Electrical	2.60 (.15)	1.22 (.02)	.17 (.01)	.19 (.01)	.42 (.01)
Food	1.59 (.36)	1.28 (.13)	.15 (.06)	.11 (.01)	.65 (.06)
General Machines	2.50 (.14)	1.22 (.03)	.17 (.02)	.14 (.01)	.55 (.01)
Iron & Steel	3.21 (.56)	1.00 (.06)	.48 (.05)	.09 (.01)	.36 (.04)
Leather & Fur	2.15 (.70)	0.76 (.14)	.07 (.05)	.18 (.02)	.53 (.06)
Metal Products	3.20 (.24)	1.10 (.03)	.31 (.05)	.13 (.01)	.40 (.02)
Non-ferrous Metal	2.89 (.38)	1.15 (.05)	.17 (.02)	.10 (.01)	.58 (.01)
Non-metal Products	2.02 (.16)	1.25 (.04)	.14 (.08)	.19 (.04)	.45 (.05)
Paper	6.25 (3.8)	0.73 (.11)	.09 (.02)	.25 (.01)	.41 (.01)
PC & AV	2.21 (.14)	1.41 (.04)	.15 (.01)	.19 (.01)	.39 (.01)
Plastic	3.51 (.29)	1.08 (.03)	.22 (.03)	.17 (.01)	.36 (.02)
Precision Tools	2.34 (.18)	1.43 (.05)	.17 (.01)	.18 (.01)	.44 (.01)
Specific Machines	1.63 (.18)	1.43 (.07)	.12 (.02)	.20 (.01)	.43 (.01)
Textile	3.73 (.36)	0.95 (.03)	.01 (.04)	.14 (.01)	.59 (.03)
Wood	1.52 (.22)	1.62 (.17)	.20 (.15)	.14 (.03)	.49 (.07)

Bootstrapped standard errors reported in parentheses.

While the capital coefficients may seem low, they are not out of line with other estimates which specifically account for material inputs (e.g. Javorcik (2004)). For the specific case of China, there are few comparable studies.[42,43]

In comparison with our findings, Brandt, Van Biesebroeck, and Zhang (2012) estimate the total factor productivity of Chinese manufacturing firms in 1998-2007 using both the Olley–Pakes and Ackerberg-Caves-Frazer estimation methods. Their results suggest that there are decreasing returns to scale in almost all industries in China. Their average sum of input intensities are 0.8 for Olley-Pakes and 0.7 for Ackerberg-Caves-Frazer, and the average sum of input intensities in our case is 0.8, in line with their higher range. Brandt et al. argue that measurement error and price setting power are plausible explanations for the low estimates, although this issue is not addressed in their paper due to the lack of firm-level price information (e.g. using the method of De Loecker (2011)), a limitation we also face.

[42] Though not directly comparable, macroeconomic estimates include Chow (1993) and Ozyurt (2009) who find higher capital coefficients. These studies do not account for materials. The most comparable study is Fleisher and Wang (2004) who find microeconomic estimates for α_K in the range of .40 to .50 (they do not differentiate between capital and materials) and this compares favorably with the combined estimates of $\alpha_K + \alpha_M$ in Table 2.

[43] We interpret the second stage estimates for Textiles with caution as capital and materials may have increased in anticipation of the Multifibre Arrangement expiring in 2005, at the end of which Chinese exports grew by over 100% in many categories. We have excluded the Apparel and Man-Made Fibre industries for this reason as they additionally fail the model restriction $\beta \geq 0$.

6.1.3 Robustness: Instrumenting Manufacturing Labor Market Conditions

To address potential simultaneity issues between the relative demand for worker types and the local supply or wages of workers, we instrument worker wages and availability ($w_{R,i}$ and $a_{R,i}$) by service sector wages, unemployment and workforce shares. While outside the scope of our model, the idea here is that service sector workers are likely somewhat mobile into manufacturing employment and thus service sector labor market conditions are likely correlated with those in manufacturing. However, it is unlikely that aggregate labor market conditions in the service sector would influence individual manufacturing firm's workforce decisions beyond the effects they have on manufacturing wages and availability. The results (see Appendix) do not drastically change the point estimates of structural model parameters which are the basis for our subsequent analysis, while the standard errors of structural estimates increase.

6.1.4 Robustness: Firm Size and Input Complementarity

As the optimal distribution of worker types within a firm might change with firm size, and because different worker types might have different complementarities with other inputs such as capital and materials, we have run two robustness checks of our first stage. The first check interacts each worker type with the logarithm of the number of employees as a measure of firm size (reported in the third and fourth column of Table A.10, see Appendix). The second check interacts each worker type with capital and material intensity as measured by the logarithm of capital and materials per worker (reported in the fifth and sixth column of Table A.10, see Appendix). The estimates are robust to these extended specification: the changes in estimates are small and generally not significant, as seen by comparing the results with the baseline specification of Table A.10 in the first and second columns.

6.1.5 Robustness: Unobserved Regional Heterogeneity

One potential concern is bias in the second stage due to omitted variables which influence input usage across regions separate from our model or observable controls. To address this, following the productivity estimation literature and noting that among inputs, capital stocks are likely slower to adjust to idiosyncratic differences (e.g. productivity, prices) than material and labor inputs, we adopt a prefecture-industry level IV strategy. We instrument firm level unit labor costs and the logarithm of material costs using the average unit labor cost and average (log) material costs at the prefecture-industry level. The second stage estimates, which allow us to quantify the productivity differences implied by the unit labor costs, are broadly similar (for a comparison, see Table A.11 in the Appendix).

6.2 Implied Productivity Differences Across Firms

Table 3 quantifies the implied differences in unit labor costs. The c_R^T column displays the interquartile (75%/25%) unit labor cost ratios by industry where unit labor costs have been calculated according to the model, and range from about 30 to 80 percent cost differences within industry. The $\left(c_R^T\right)^{\alpha_L^T}$ column takes into account substitution into non-labor inputs and range from about 3 to 12 percent. For example, consider two firms in General Machines at the 25th and 75th unit labor cost percentile. If both firms have the same wage bill, the labor (L) available to the lower cost firm is 1.41 times greater than the higher cost firm. From Table 2 above, the estimated share of wages in production is $\alpha_L^T = .17$, so the lower cost firm will produce $1.41^{.17} = 1.06$ times as much output as the higher cost firm, holding all else constant.

Table 3: Intraindustry Unit Labor Cost Ratios

Industry	c_R^T $^{75}/_{25}$	$\left(c_R^T\right)^{\alpha_L^T}$ $^{75}/_{25}$	Industry	c_R^T $^{75}/_{25}$	$\left(c_R^T\right)^{\alpha_L^T}$ $^{75}/_{25}$
Beverage	1.51	1.08	Non-metal Products	1.42	1.06
Electrical	1.38	1.06	Paper	1.66	1.08
Food	1.81	1.09	PC & AV	1.44	1.03
General Machines	1.41	1.06	Plastic	1.35	1.07
Iron & Steel	1.34	1.15	Precision Tools	1.80	1.09
Leather & Fur	1.92	1.05	Specific Machines	1.99	1.09
Metal Products	1.33	1.05	Textile	1.37	1.00
Non-ferrous Metal	1.45	1.12	Wood	1.47	1.08

Table 3 indicates that the range of total unit costs faced by firms within the same industry are indeed substantial, even after explicitly taking into account the technology θ^T and the ability to substitute across several types of local workers. However, the second stage estimates indicate these differences are attenuated by substitution into capital and materials. Thus, while differences in regional markets indicate an interquartile range of 30-80% in unit cost differences, substitution into other factors reduces this range to between 3-12%.

Table 4 displays similar calculations for capital and materials. The $\kappa_R^{\alpha_K^T}$ and $\mu_R^{\alpha_M^T}$ columns display the interquartile ratio of capital and material quality, ranging from about 1 to 3 percent for capital and 2 to 5 percent for materials. Clearly estimated differences in labor markets are substantially wider, in part due to the fact that we observe more information about workers than types of capital or materials. Finally, the u_R^T column contains the differences in productivity implied by regional cost differences as laid out in Section 2.4.

Table 4: Intraindustry Capital, Material and Productivity Ratios

Industry	$\kappa_R^{\alpha_K^T}$ $^{75}/_{25}$	$\mu_R^{\alpha_M^T}$ $^{75}/_{25}$	u_R^T $^{75}/_{25}$	Industry	$\kappa_R^{\alpha_K^T}$ $^{75}/_{25}$	$\mu_R^{\alpha_M^T}$ $^{75}/_{25}$	u_R^T $^{75}/_{25}$
Beverage	1.01	1.05	1.10	Non-metal Products	1.01	1.05	1.09
Electrical	1.02	1.04	1.07	Paper	1.02	1.04	1.10
Food	1.01	1.05	1.10	PC & AV	1.03	1.04	1.06
General Machines	1.01	1.04	1.08	Plastic	1.02	1.02	1.09
Iron & Steel	1.01	1.02	1.15	Precision Tools	1.02	1.03	1.08
Leather & Fur	1.01	1.03	1.08	Specific Machines	1.02	1.03	1.09
Metal Products	1.02	1.04	1.07	Textile	1.01	1.03	1.05
Non-ferrous Metal	1.01	1.03	1.12	Wood	1.01	1.04	1.08

Table 5 examines the variance of productivity by industry under the unit cost method (Column 1) compared to estimating output by a Cobb-Douglas combination of capital, materials and the number of each worker type (Column 2). Column 3 of Table 5 shows the average percentage that unexplained productivity is reduced per firm under the unit labor cost method.[44] As shown by the Table, the variance of unexplained productivity is reduced by about 6 to 30 percent once local factor markets are explicitly accounted for, showing that this approach does indeed provide more information about the determinants of firm productivity, with the relative importance of inputs indicated by Tables 3 and 4.

Table 5: Percentage of Productivity Explained by Unit Cost Method

Industry	Unit Cost σ^2	Four Types σ^2	Average Percent Reduced	Industry	Unit Cost σ^2	Four Types σ^2	Average Percent Reduced
Beverage	.39	.54	.20	Non-metal Products	.30	.43	.18
Electrical	.50	.67	.14	Paper	.44	.56	.12
Food	.44	.59	.15	PC & AV	.86	.94	.13
General Machines	.34	.46	.17	Plastic	.43	.65	.23
Iron & Steel	.19	.66	.49	Precision Tools	.56	.69	.14
Leather & Fur	.43	.46	.04	Specific Machines	.50	.61	.07
Metal Products	.45	.61	.18	Textile	.43	.45	.06
Non-ferrous Metal	.32	.64	.30	Wood	.31	.45	.19

We next quantify the net impact of these productivity differences across China by evaluating the change in real income consumers would experience if labor markets were homogeneous.

[44]Most models used in production estimation assume perfect labor substitutability. Such models imply that, conditional on wages, the local composition of the workforce is irrelevant for hiring. The approach of this paper incorporates local factor supply and an empirical comparison with other models is presented in Appendix C.2.

6.3 Consumer Welfare and Local Factor Market Costs

We now consider a hypothetical Chinese economy in which the distribution of workers and wages across regions is equalized to the national average for each worker type. This is of course an unrealistic assumption given the myriad influences of workers' location decisions, but does provide a benchmark to quantify the welfare impacts of homogenizing labor costs across China, and thus the importance of factor markets.

Letting $\left\{u_R^T\right\}$ be the estimated unit costs for China, $\mathbb{P}_R$ the population of manufacturing workers in region R and σ^T the share of consumption for each industry T as given by the 2002 Input-Output Tables for China, Equation (3.3) can be computed for new unit costs $\left\{v_R^T\right\}$. To arrive at $\left\{v_R^T\right\}$, we use our model parameter estimates while assuming that each region contains the nationally averaged frequency of each worker type who receives the nationally averaged wage for their type. This implies a more even distribution of worker types and wages that will reallocate expenditure across regions and industries in potentially advantageous ways. In particular, more firms will enter into areas where costs drop and will exit areas where costs rise. Calculation of Equation (3.3) yields a real income gain of 1.33 percent under our baseline estimates, and 1.11 percent under our instrumental variables estimates.[45] This suggests that while factor market differences are large, if firms relocate in response to these new conditions as in our model, the net welfare gains are in line with other estimates of the gains from trade for large countries.

Since firms locate freely, the model predicts that these substantial cost differences drive economic activity towards more advantageous locations, which we now examine.

6.4 Aggregate Firm Location

Per capita volumes of economic activity across regions are determined by Equation (3.7), which states that relatively lower industry labor costs should attract relatively more firms to a region. Due to a lack of panel data or instruments which might convincingly address confounding empirical issues such as the role of Chinese industrial policy or the joint determination of firm and worker location (beyond the relationships explained by the model), we interpret our results as a quantification of model relationships, rather than a causal relationship. Table 6 summarizes estimates of this relationship, controlling for regional distance to the nearest city (weighted by the share of log value added in a region).[46] A firm's distance from a city may explain many factors, and above we have seen firms closer to cities have relatively higher capital and material quality. Even controlling for geography, the impact of advantageous labor markets still often remains. Whenever the relation-

[45] Since unit costs in fact vary at the firm level, we use the employment weighted average of firm unit costs in each region-industry pair.

[46] Rizov and Zhang (2013) find that aggregate productivity is higher in regions with high population density, and the theory of this paper implies productivity drives increased entry.

ship between value added and labor costs is statistically significant, the relationship is negative, in line with the model.[47] While the point estimates vary, the median significant estimate is about -.7, indicating a 10% increase in unit labor costs is associated with an 7% decrease in value added per capita.

Table 6: Determinants of Regional (Log) Value Added per Capita

Industry	$\ln\left(c_R^T\right)$	Std Err	100 km to City	Std Err	Const	Std Err	Obs	R^2
Beverage	-0.671***	(.241)	-0.099	(.097)	18.74***	(2.936)	155	.035
Electrical	0.229	(.376)	-0.769***	(.120)	8.84*	(4.489)	166	.253
Food	-0.555**	(.219)	-0.439***	(.113)	15.82***	(2.070)	171	.108
General Machines	-0.408	(.351)	-0.776***	(.120)	16.39***	(4.247)	195	.206
Iron & Steel	-0.880	(.609)	-0.426***	(.132)	15.07***	(2.396)	160	.080
Leather & Fur	-1.052***	(.262)	-0.554***	(.159)	23.60***	(3.177)	89	.300
Metal Products	0.049	(.383)	-0.769***	(.113)	10.58***	(4.014)	157	.260
Non-ferrous Metal	-2.096***	(.430)	-0.534***	(.119)	28.64***	(3.610)	139	.199
Non-metal Products	-0.423	(.281)	-0.495***	(.070)	16.39***	(3.270)	259	.155
Paper	-0.806***	(.200)	-0.354***	(.121)	19.12***	(2.099)	159	.155
PC & AV	-0.611**	(.279)	-1.037***	(.152)	19.66***	(3.506)	90	.318
Plastic	0.007	(.334)	-0.671***	(.104)	10.66***	(3.773)	159	.209
Precision Tools	-0.271	(.274)	-0.677***	(.156)	13.51***	(3.109)	68	.170
Specific Machines	-0.238	(.177)	-0.452***	(.094)	14.01***	(2.190)	167	.121
Textile	-0.623**	(.292)	-0.777***	(.099)	17.26***	(2.584)	186	.260
Wood	-2.020***	(.313)	-0.567***	(.165)	43.74***	(5.214)	133	.215

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

6.5 Labor Markets and China's WTO Accession

As a counterfactual exercise, we consider the impact of improved access to US markets arising from a structural shift in trade policy, namely China's WTO membership in 2001. China's permanent normal trade relations with the US reduced the expected tariffs faced by Chinese exporters in the face of potential non-renewal of MFN status by the US Congress (see Justin Pierce and Peter Schott (2016) for more details).[48] We measure the effect of this policy change on labor markets at the prefecture level, for all prefectures which have obtained 'city' status (207 prefectures) and therefore appear in both the 1999 China City Statistical Yearbook and 1998 Annual Industrial Survey. This allows us to aggregate the reduction in expected tariffs at the prefecture level using the Bartik (1991) composition method. We construct a 4 digit ISIC tariff gap measure for each

[47] These results are robust if distance is unweighted, and to the inclusion of Economic Zone status.

[48] Pierce and Schott argue that US tariff gaps are plausibly exogenous to outcomes in China as 89% of the variation in tariff gap is from the variation in Smoot-Hawley tariffs which were set 70 years prior to China's WTO accession.

industry T, TariffGap_T,[49] and weight the impact of TariffGap_T by the employment share of each industry in prefecture R in 1998 to arrive at the regional treatment

$$\text{TariffGapRegion}_R \equiv \sum_T \text{Employment Share}_{TR} \cdot \text{TariffGap}_T.$$

We use TariffGapRegion_R to predict changes in the population share of worker types in each region between 2000 and 2005 due to WTO accession using local linear estimates as presented in Figure A.1 of the Appendix.[50]

We use the predicted population share changes to predict the skill distribution of prefectures if China had not acceded to the WTO. We then recalculate the unit labor costs and productivity for each firm and compare the dispersion of these counterfactuals with the actual dispersion as presented in Table A.12 of Appendix F. While the interquartile unit cost ratios do vary slightly under the two scenarios, the interquartile productivity ratios are essentially identical across the two scenarios.[51] There are only slightly larger differences at the 90/10 and 95/5 percentiles, indicating that while skill distributions of workers were effected by China's WTO accession, relative productivity distributions of firms were essentially unchanged.

7 Conclusion

This paper examines the importance of local supply characteristics in determining firm input usage and productivity. To do so, a theory and empirical method are developed to identify firm input demand across industries and heterogeneous labor markets. The model derives labor demand as driven by the local distribution of wages and available skills. Firm behavior in general equilibrium is derived, and determines firm location as a function of regional costs. This results in an estimator which can be easily implemented in two steps. The first step exploits differences in firm hiring patterns across distinct regional factor markets to recover firm labor demand by type, and similarly, differences in regional factor quality. These estimates quantify local unit labor costs and combine otherwise disparate data sets on firms and labor markets into a unified framework. The second step introduces local factor market costs into production function estimation. Both steps characterize the impact of local market conditions on firm behavior through recovery of model primitives. This is of particular interest when explaining the relative productivity or location of firms, especially in

[49] Defined as the simple average of HS- 6 product-level tariff gaps averaged to the 4 digit ISIC level, using the UN Statistics concordance.

[50] Note we have no wage data by type for the year 2000 so have no similar way of performing a counterfactual for wages by type.

[51] With the exception of the Iron and Steel sector which has an interquartile productivity ratio of 1.15 vs 1.14 under trade policy uncertainty.

settings where local characteristics are highly dissimilar.

Applying the model framework to China, which possesses a large number of distinct and varied factor markets shows this approach uncovers substantial determinants of firm heterogeneity. Estimates imply an interquartile difference in labor costs of 30 to 80 percent and productivity differences of 3 to 12 percent. Differences in capital and material quality explain similar interquartile differences. The results illustrate that local factor market conditions explain substantial differences in firm workforce composition, input use and productivity. This is underscored by the estimate that complete homogenization of labor markets would lead to a 1.33 percent increase in real income for Chinese consumers as firms adapt to local factor market conditions. In addition, the variance of unexplained productivity is reduced by 6 to 30 percent compared to a standard estimation approach which does not account for local factor markets. Modeling a firm's local environment yields substantial insights into production patterns that are quantitatively important.

The importance of local factor markets for understanding firm behavior suggests new dimensions for policy analysis. For instance, regions with labor markets which generate lower unit labor costs tend to attract higher levels of firm activity within an industry. As unit labor costs depend on rather the distribution of wages *and* worker types that represent substitution options, this yields a deeper view of how educational policy or flows of different worker types impact firms. For this reason, work evaluating wage determination could be enriched by taking this approach.[52] Taken as a whole, the results show that policy changes which influence the composition of regional labor markets will likely have sizable effects on firm productivity and location. Finally, the substantial differences *within industry* suggest that at the regional level, inherent comparative advantages exist which policymakers might leverage.[53]

Furthermore, as pointed out by Ottaviano and Peri (2013), little is known about the dynamic relationships between labor markets and firm behavior, and this paper provides both a general equilibrium theory and structural estimation strategy to evaluate these linkages.[54] Having seen that cost and productivity differences inherent in local factor markets are potentially large, our approach could be of use in evaluating trade offs between regional policies or ongoing trends across regions. Finally, nothing precludes the application of this paper's approach beyond China, and it is suitable for analyzing regions which exhibit a high degree of labor market heterogeneity. Further work could leverage or extend the approach of combining firm, census and geographic data

[52] There is large literature following Hellerstein, Neumark, and Troske (1999). For instance, Van Biesebroeck (2011) find the usual relationship between wages and marginal productivity breaks down in less developed countries. Investigating this relationship using our approach could shed light on regional determinants of labor market clearing, for instance evaluating gender differentials as in Dong and Zhang (2009).

[53] For a discussion of broader policy implications of regional differences in production, see Luger and Evans (1988).

[54] Early results suggest firm entry is responsive to labor market changes, especially in manufacturing (Olney, 2013), and labor costs are known to strongly influence vertical production networks (Hanson, Mataloni Jr, and Slaughter, 2005).

to better understand the role of local factor markets on firm behavior.

References

ABOWD, J. M., J. HALTIWANGER, R. JARMIN, J. LANE, P. LENGERMANN, K. MCCUE, K. MCKINNEY, AND K. SANDUSKY (2005): "The Relation among Human Capital, Productivity, and Market Value: Building Up from Micro Evidence," in *Measuring Capital in the New Economy*, NBER Chapters, pp. 153–204. National Bureau of Economic Research.

ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High Wage Workers and High Wage Firms," *Econometrica*, 67(2), pp. 251–333.

AFRIDI, F., S. LI, AND Y. REN (2012): "Social Identity and Inequality: The Impact of China's Hukou System," *Working Paper*.

ATALAY, E., A. HORTACSU, AND C. SYVERSON (2012): "Why Do Firms Own Production Chains?," NBER Working Papers 18020, National Bureau of Economic Research, Inc.

AUTOR, D., D. DORN, AND G. H. HANSON (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *The American Economic Review*, 103(6), 2121–2168.

BANDIERA, O., I. BARANKAY, AND I. RASUL (2009): "Social Connections and Incentives in the Workplace: Evidence from Personnel Data," *Econometrica*, 77(4), pp. 1047–1094.

BARTIK, TIMOTHY J. (1991): *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute for Employment Research, Kalamazoo, MI.

BAS, M., AND V. STRAUSS-KAHN (2015): "Input-trade Liberalization, Export Prices and Quality Upgrading," *Journal of International Economics*, 95(2), 250–262.

BAUM-SNOW, N., L. BRANDT, J. V. HENDERSON, M. A. TURNER, AND Q. ZHANG (2017): "Roads, Railroads and Decentralization of Chinese Cities," *The Review of Economics and Statistics*, 99(3), 435–448.

BERNARD, A., S. REDDING, AND P. SCHOTT (2007): "Comparative Advantage and Heterogeneous Firms," *Review of Economic Studies*, 74(1), 31–66.

BERNARD, A. B., S. J. REDDING, AND P. K. SCHOTT (2013): "Testing for Factor Price Equality with Unobserved Differences in Factor Quality or Productivity," *American Economic Journal: Microeconomics*, 5(2), 135–163.

BERNHOFEN, D. M., AND J. C. BROWN (2011): "Testing the General Validity of the Heckscher-Ohlin Theorem: The Natural Experiment of Japan," CESifo Working Paper Series 3586, CESifo Group Munich.

BERNSTEIN, J. R., AND D. E. WEINSTEIN (2002): "Do Endowments Predict the Location of Production?: Evidence from National and International Data," *Journal of International Economics*, 56(1), 55–76.

BLOOM, N., AND J. V. REENEN (2007): "Measuring and Explaining Management Practices across Firms and Countries," *The Quarterly Journal of Economics*, 122(4), pp. 1351–1408.

BLOOM, N., M. SCHANKERMAN, AND J. VAN REENEN (2013): "Identifying Technology Spillovers and Product Market Rivalry," *Econometrica*, 81(4), 1347–1393.

BOMBARDINI, M., G. GALLIPOLI, AND G. PUPATO (2012): "Skill Dispersion and Trade Flows," *The American Economic Review*, 102(5), 2327–2348.

BORJAS, G. J. (2003): "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market," *The Quarterly Journal of Economics*, 118(4), 1335–1374.

BORJAS, G. J. (2013): "The Analytics of the Wage Effect of Immigration," *IZA Journal of Migration*, 2(1), 2–22.

BOWLES, S. (1970): "Aggregation of Labor Inputs in the Economics of Growth and Planning: Experiments with a Two-Level CES Function," *The Journal of Political Economy*, 78(1), 68–81.

BRANDT, L., T. TOMBE, AND X. ZHU (2013): "Factor Market Distortions Across Time, Space and Sectors in China," *Review of Economic Dynamics*, 16(1), 39–58.

BRANDT, L., J. VAN BIESEBROECK, AND Y. ZHANG (2012): "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, (97).

BROWN, J. D., J. L. HOTCHKISS, AND M. QUISPE-AGNOLI (2013): "Does Employing Undocumented Workers Give Firms A Competitive Advantage?," *Journal of Regional Science*, 53(1), 158–170.

CARL DAVIDSON, FREDRIK HEYMAN, STEVEN MATUSZ, FREDRIK SJOHOLM, AND SUSAN ZHU (2013): "Globalization and the Organization of the Firm," *Working Paper*.

CHAN, K. W. (2013): "China, Internal Migration," in *The Encyclopedia of Global Human Migration*, ed. by Bellwood, Peter. Wiley Online Library.

CHAN, K. W., AND W. BUCKINGHAM (2008): "Is China Abolishing the Hukou System?," *The China Quarterly*, 195, 582–606.

CHAN, K. W., T. LIU, AND Y. YANG (1999): "Hukou and Non-hukou Migrations in China: Comparisons and Contrasts," *International Journal of Population Geography*, 5, 425–448.

CHOW, G. C. (1993): "Capital Formation and Economic Growth in China," *The Quarterly Journal of Economics*, 108, 809–842.

CINGANO, F., AND F. SCHIVARDI (2004): "Identifying the Sources of Local Productivity Growth," *Journal of the European Economic Association*, 2(4), 720–744.

DE LOECKER, J. (2011): "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 79(5), 1407–1451.

Defever, F., and A. Riano (2017): “Subsidies with Export Share Requirements in China,” *Journal of Development Economics*, 126, 33–51.

Dhingra, S., and J. Morrow (2012): “Monopolistic Competition and Optimum Product Diversity Under Firm Heterogeneity,” *London School of Economics, mimeograph.*

Dong, X.-Y., and L. Zhang (2009): “Economic Transition and Gender Differentials in Wages and Productivity: Evidence from Chinese Manufacturing Enterprises,” *Journal of Development Economics*, 88(1), 144–156.

Dustmann, C., and A. Glitz (2015): “How do Industries and Firms Respond to Changes in Local Labor Supply?,” *Journal of Labor Economics*, 33(3), 711–750.

Faber, B. (2014): “Trade Integration, Market Size, and Industrialization: Evidence from China’s National Trunk Highway System,” *Review of Economic Studies*, 81(3), 1046–1070.

Fadinger, H. (2011): “Productivity Differences in an Interdependent World,” *Journal of International Economics*, 84(2), 221–232.

Fitzgerald, D., and J. C. Hallak (2004): “Specialization, Factor Accumulation and Development,” *Journal of International Economics*, 64(2), 277–302.

Fleisher, B. M., and X. Wang (2004): “Skill Differentials, Return to Schooling, and Market Segmentation in a Transition Economy: the Case of Mainland China,” *Journal of Development Economics*, 73(1), 315–328.

Fox, J. T., and V. Smeets (2011): “Does Input Quality Drive Measured Differences in Firm Productivity?,” *International Economic Review*, 52(4), 961–989.

Garicano, L., and P. Heaton (2010): “Information Technology, Organization, and Productivity in the Public Sector: Evidence from Police Departments,” *Journal of Labor Economics*, 28(1), 167–201.

Ge, S., and D. T. Yang (2014): “Changes in China’s Wage Structure,” *Journal of the European Economic Association*, 12(2), 300–336.

Gonzalez, L., and F. Ortega (2011): “How Do Very Open Economies Adjust to Large Immigration Flows? Evidence from Spanish Regions,” *Labour Economics*, 18(1), 57–70.

Grossman, G. M., and G. Maggi (2000): “Diversity and Trade,” *The American Economic Review*, 90(5), 1255–1275.

Guiso, L., L. Pistaferri, and F. Schivardi (2013): “Credit within the Firm,” *The Review of Economic Studies*, 80(1), 211–247.

Hanson, G. H., R. J. Mataloni Jr, and M. J. Slaughter (2005): “Vertical Production Networks in Multinational Firms,” *Review of Economics and Statistics*, 87(4), 664–678.

HELLERSTEIN, J. K., D. NEUMARK, AND K. R. TROSKE (1999): "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations," *Journal of Labor Economics*, 17(3), 409–446.

HELPMAN, E., O. ITSKHOKI, AND S. REDDING (2010): "Inequality and Unemployment in a Global Economy," *Econometrica*, 78(4), 1239–1283.

HIRSCHMAN, A. (1958): *The Strategy of Economic Development.* Yale University Press, New Haven.

HORTAÇSU, A., AND C. SYVERSON (2007): "Cementing Relationships: Vertical Integration, Foreclosure, Productivity, and Prices," *Journal of Political Economy*, 115(2), 250–301.

HSIEH, C. T., AND P. J. KLENOW (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4), 1403–1448.

ILMAKUNNAS, P., AND S. ILMAKUNNAS (2011): "Diversity at the Workplace: Whom Does it Benefit?," *De Economist*, 159(2), 223–255.

INFORMATION OFFICE OF THE STATE COUNCIL OF THE PEOPLE'S REPUBLIC OF CHINA (2005): "Regional Autonomy for Ethnic Minorities in China," *Chinese government's official web portal*.

IRANZO, S., F. SCHIVARDI, AND E. TOSETTI (2008): "Skill Dispersion and Firm Productivity: An Analysis with Employer-Employee Matched Data," *Journal of Labor Economics*, 26(2), 247–285.

JAVORCIK, B. S. (2004): "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages," *American Economic Review*, 94(3), 605–627.

JUSTIN PIERCE, AND PETER SCHOTT (2016): "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, 106(7), 1632–62.

KARADI, P., AND M. KOREN (2012): "Cattle, Steaks and Restaurants: Development Accounting when Space Matters," *Working Paper*.

KENNAN, J., AND J. R. WALKER (2011): "The Effect of Expected Income on Individual Migration Decisions," *Econometrica*, 79(1), 211–251.

KUGLER, M., AND E. VERHOOGEN (2011): "Prices, Plant Size, and Product Quality," *The Review of Economic Studies*, 79(1), 307–339.

LAZEAR, E. P. (2000): "Performance Pay and Productivity," *The American Economic Review*, 90(5), pp. 1346–1361.

LUGER, M. I., AND W. N. EVANS (1988): "Geographic Differences in Production Technology," *Regional Science and Urban Economics*, 18(3), 399–424.

MA, Y., H. TANG, AND Y. ZHANG (2014): "Factor intensity, product switching, and productivity: Evidence from Chinese exporters," *Journal of International Economics*, 92(2), 349–362.

MANNING, A. (2011): "Imperfect Competition in the Labor Market," *Handbook of Labor Economics*, 4, 973–1041.

MANOVA, K., AND Z. ZHANG (2012): "Export Prices Across Firms and Destinations," *The Quarterly Journal of Economics*, 127(1), 379–436.

MARTINS, P. S. (2008): "Dispersion in Wage Premiums and Firm Performance," *Economics Letters*, 101(1), 63–65.

MELITZ, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.

MELITZ, M. J., AND S. J. REDDING (2014): "Heterogeneous Firms and Trade," *Handbook of International Economics*, 4, 1–54.

MORETTI, E. (2004): "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions," *American Economic Review*, 94(3), 656–690.

——— (2011): "Chapter 14 - Local Labor Markets," vol. 4, Part B of *Handbook of Labor Economics*, pp. 1237 – 1313. Elsevier.

MORROW, J. (2010): "Is Skill Disperison a Source of Productivity and Exports in Developing Countries?," *Working Paper*.

NISHIOKA, S. (2012): "International Differences in Production Techniques: Implications for the Factor Content of Trade," *Journal of International Economics*, 87(1), 98–104.

OLNEY, W. W. (2013): "Immigration and Firm Expansion," *Journal of Regional Science*, 53(1), 142–157.

OTTAVIANO, G., AND G. PERI (2013): "New Frontiers of Immigration Research: Cities and Firms," *Journal of Regional Science*, 53(1), 1–7.

OTTAVIANO, G. I., AND G. PERI (2012): "Rethinking the Effect of Immigration on Wages," *Journal of the European Economic Association*, 10(1), 152–197.

OVERMAN, H. G., AND D. PUGA (2010): "Labor Pooling as a Source of Agglomeration: An Empirical Investigation," in *Agglomeration Economics*, ed. by Edward L. Glaeser. University of Chicago Press.

OZYURT, S. (2009): "Total Factor Productivity Growth in Chinese Industry: 1952-2005," *Oxford Development Studies*, 37(1), 1–17.

PARROTTA, P., D. POZZOLI, AND M. PYTLIKOVA (2011): "Does Labor Diversity affect Firm Productivity?," Norface Discussion Paper Series 2011022, Norface Research Programme on Migration, Department of Economics, University College London.

——— (2014): "Labor Diversity and firm Productivity," *European Economic Review*, 66, 144–179.

RIZOV, M., AND X. ZHANG (2013): "Regional Disparities and Productivity in China: Evidence from Manufacturing Micro Data," *Papers in Regional Science*.

SYVERSON, C. (2004): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(6), 1181–1222.

——— (2011): "What Determines Productivity?," *Journal of Economic Literature*, 49(2), 326–365.

TOLBERT, C., AND M. SIZER (1996): *U.S. Commuting Zones and Labor Market Outcomes: A 1990 Update*. Economic Research Service, U.S. Department of Agriculture.

TOPALOVA, P. (2010): "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics*, 2(4), 1–41.

TREFLER, D. (1993): "International Factor Price Differences: Leontief was Right!," *Journal of Political Economy*, pp. 961–987.

VAN BIESEBROECK, J. (2011): "Wages Equal Productivity. Fact or Fiction? Evidence from Sub Saharan Africa," *World Development*, 39(8), 1333–1346.

VANEK, J. (1968): "The Factor Proportions Theory: The N-Factor Case," *Kyklos*, 21(4), 749–756.

ZHANG, X., J. YANG, AND S. WANG (2011): "China has Reached the Lewis Turning Point," *China Economic Review*, 22(4), 542–554.

Appendix

The organization of the Appendix is as follows: Section A contains proofs of results discussed in the main text. Section B evaluates the efficacy of the reduced form model estimator. Section C contains more detail regarding model estimates. Three supplemental appendices are provided for online publication: Section G contains additional details on the model solution and properties. Section H contains supplemental summary statistics and empirical results.

A Proofs

Proposition. *If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers.*

Proof. Let c_R^T denote a firm's unit labor cost when all worker types are hired, and $\check{c}_R^T$ the unit labor cost if a subset of types $\mathbb{T} \subset \{1, \ldots \mathbb{S}\}$ is hired. For the result, we require that $c_R^T \leq \check{c}_R^T$ for all $\mathbb{T}$.

Considering a firm's cost minimization problem when $\mathbb{T}$ are the only types available shows with Equation (2.4) that

$$\check{c}_R^T = \left[\sum_{i \in \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} / f\left(k-1\right) \right]^{\theta^T/\beta^T} \right]^{\left(\beta^T/\theta^T\right)/(1-k)} .$$

Considering then that

$$c_R^T / \check{c}_R^T = \left[1 + \left(\sum_{i \notin \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} \right]^{\theta^T/\beta^T} / \sum_{i \in \mathbb{T}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} \right]^{\theta^T/\beta^T} \right) \right]^{\left(\beta^T/\theta^T\right)/(1-k)} ,$$

clearly $c_R^T \leq \check{c}_R^T$ so long as $\beta^T/\theta^T\,(1-k) \leq 0$, which holds for $\beta^T > 0$ since $k > 1$. □

Proposition. *An equilibrium wage vector exists which clears each regional labor market.*

Proof. What is required is to exhibit a wage vector $\{w_{R,i}\}$ that ensures Equation (3.6) holds. To do so, first note that the resource clearing conditions determine wages, provided an exogenous vector of unit labor costs $\left\{c_R^T\right\}$. Since all prices are nominal, WLOG we normalize $\mathbb{I} = 1$ in the following

Lemma. *There is a wage function that uniquely solves (3.6) given unit labor costs.*

Proof. Formally, we need to exhibit $\mathbb{W}$ such that

$$a_{R,i} = \mathbb{W}_{R,i}\left(\left\{c_{R'}^{T'}\right\}\right)^{-1} \sum_t \alpha_L^t \sigma^t \left(c_R^t\right)^{k/\beta^t - 1} \left(\frac{\mathbb{W}_{R,i}\left(\left\{c_{R'}^{T'}\right\}\right)^{1-k} a_{R,i}\left(\underline{m}_i^t\right)^k}{f\left(k-1\right)} \right)^{\theta^t/\beta^t} \quad \forall R, i.$$

Fix $\left\{c_{R'}^{T'}\right\}$ and define $h_{R,i}(x) \equiv \sum_t \alpha_L^t \sigma^t \left(c_R^t\right)^{k/\beta^t-1} \left(x^{1-k} a_{R,i} \left(\underline{m}_i^t\right)^k / f\left(k-1\right)\right)^{\theta^t/\beta^t}$, $g_{R,i}(x) \equiv a_{R,i} x$. For the result we require a unique x s.t. $g_{R,i}(x) = h_{R,i}(x)$. $g_{R,i}$ is strictly increasing and ranges from 0 to ∞, while $h_{R,i}(x)$ is strictly decreasing, and ranges from ∞ to 0, so x exists and is unique. □

Of course, unit labor costs are not exogenous as in the Lemma, but rather depend on endogenous wages $\{w_{R,i}\}$. However, the lemma does show that the following mapping:

$$\{w_{R,i}\} \underset{\text{Equation 2.4}}{\mapsto} \left\{c_R^T\left(\{w_{R,i}\}\right)\right\} \underset{\text{Lemma}}{\mapsto} \mathbb{W}\left(\left\{c_R^T\left(\{w_{R,i}\}\right)\right\}\right),$$

which starts at one wage vector $\{w_{R,i}\}$ and ends at another wage vector $\mathbb{W}$ is well defined. The result follows if we can show the function $\left\{c_R^T \circ \mathbb{W}\left(\left\{c_R^T\right\}\right)\right\}$, where c_R^T is the unit cost function of Equation (2.4), has a fixed point $\left\{\widehat{c}_R^T\right\}$ and so $\mathbb{W}\left(\left\{\widehat{c}_R^T\right\}\right)$ is a solution to Equation (3.6).

We first show that any equilibrium wage vector must lie in a strictly positive, compact set $\times_{R,i}\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]$. From (3.6), $H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T}\in[0,1]$ so $w_{R,i}\leq\overline{w}_{R,i}\equiv\sum_t\alpha_L^t\sigma^t/a_{R,i}$. Let

$$\underline{b}_R\equiv\min_i\sum_t\alpha_L^t\sigma^t\left(a_{R,i}\left(\underline{m}_i^t\right)^k\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}_i^t\right)^k\right]^{\theta^t/\beta^t}a_{R,i},$$

and we will show that a lower bound for equilibrium wages is $\underline{w}_R\equiv\left[\begin{array}{ccc}\underline{b}_R, & \ldots, & \underline{b}_R\end{array}\right]$ for each R. Consider that for $\mathbb{W}$ evaluated at $\left\{c_R^T\left(\underline{w}_R\right)\right\}$,

$$\mathbb{W}_{R,i}=\sum_t\alpha_L^t\sigma^t\left(a_{R,i}\left(\underline{m}_i^t\right)^k\left(\mathbb{W}_{R,i}/\underline{w}_R\right)^{1-k}\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}_i^t\right)^k\right]^{\theta^t/\beta^t}a_{R,i}. \tag{A.1}$$

Evaluating Equation (A.1), if $\mathbb{W}_{R,i}\leq\underline{w}_R$ then $\mathbb{W}_{R,i}\geq\underline{w}_R$, and otherwise, $\mathbb{W}_{R,i}\geq\underline{w}_R$ so $\{\underline{w}_R\}$ is a lower bound for $\mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)$. Since necessarily any equilibrium wages $\hat{w}_R$ must satisfy $\mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right)=\{\hat{w}_R\}$, $\mathbb{W}$ is increasing in $\left\{c_R^T\right\}$, and $c_R^T\left(w_R\right)$ is increasing in w_R, we have $\{\hat{w}_R\}=\mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right)\geq\mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)\geq\{\underline{w}_R\}$. In conclusion, all equilibrium wages must lie in $\times_{R,i}\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]$.

Now define a strictly positive, compact domain for $\left\{c_R^T\right\}$, $\times_R\left[\underline{c}_R^T,\overline{c}_R^T\right]$, by

$$\underline{c}_R^T\equiv\inf_{\times_i\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]}c_R^T\left(w_R\right)=c_R^T\left(\underline{w}_R\right),\qquad\overline{c}_R^T\equiv\sup_{\times_i\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]}c_R^T\left(w_R\right)=c_R^T\left(\overline{w}_R\right).$$

Now consider the mapping $\mathbb{C}\left(\left\{c_R^T\right\}\right)\equiv\left\{c_R^T\circ\mathbb{W}\left(\left\{c_R^T\right\}\right)\right\}$ on $\times_R\left[\underline{c}_R^T,\overline{c}_R^T\right]$, which is continuous on this domain. By above, $\mathbb{W}_{R,i}\left(\left\{c_R^T\right\}\right)\leq\overline{w}_{R,i}$ for each R,i so $\mathbb{C}\left(\left\{c_R^T\right\}\right)\leq\left\{\overline{c}_R^T\right\}$. Also by above, $\mathbb{C}\left(\left\{c_R^T\right\}\right)\geq\left\{c_R^T\circ\mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)\right\}\geq\left\{c_R^T\left(\left\{\underline{w}_R\right\}\right)\right\}=\left\{\underline{c}_R^T\right\}$. Thus $\mathbb{C}$ maps $\times_R\left[\underline{c}_R^T,\overline{c}_R^T\right]$ into itself and by Brouwer's fixed point theorem, there exists a fixed point $\left\{\hat{c}_R^T\right\}$, which implies $\mathbb{W}\left(\left\{\hat{c}_R^T\right\}\right)$ is an equilibrium wage vector. □

Proposition. *Regions with lower factor costs have more firms per capita. In particular, if $\mathbb{F}_R^T$ denotes the mass of firms per capita in region R, industry T then*

$$\ln\left(\mathbb{F}_R^T/\mathbb{F}_{R'}^T\right)=\alpha_K^T\ln\left(\kappa_{R'}/\kappa_R\right)+\alpha_M^T\ln\left(\mu_{R'}/\mu_R\right)+\alpha_L^T\ln\left(c_{R'}^T/c_R^T\right). \tag{A.2}$$

Proof. This follows quickly from the definition of the mass of firms per capita, $\mathbb{F}_R^T=\mathbb{M}_R^T\cdot G\left(\overline{\eta}_R^T\right)/\mathbb{P}_R$, since

$$\text{Firms per Capita, R to R}':\quad\frac{\mathbb{M}_R^T\cdot G\left(\overline{\eta}_R^T\right)/\mathbb{P}_R}{\mathbb{M}_{R'}^T\cdot G\left(\overline{\eta}_{R'}^T\right)/\mathbb{P}_{R'}}=\frac{u_{R'}^T}{u_R^T}=\left(\frac{\kappa_{R'}}{\kappa_R}\right)^{\alpha_K^T}\left(\frac{\mu_{R'}}{\mu_R}\right)^{\alpha_M^T}\left(\frac{c_{R'}^T}{c_R^T}\right)^{\alpha_L^T}.$$

□

B Model Simulation and Estimator Viability

A model simulation was constructed using parameters given in Table A.1. In the simulation, firms maximize profits conditional on local market conditions, and applying the estimator above produces Tables A.2a and A.2b. The Estimate column contains results while the model values are reported in the Predicted column. The estimates are very close to the predicted values. Figure A.1 further confirms this by plotting the simulated and predicted differences in the share of workers hired. For ease of comparison, Figure A.1 plots regional frequencies along the horizontal axis and (linearly) normalized wages for each worker type. As the Figure suggests, the R^2 in both cases are high: .99 for the first stage and .97 for the second stage.

Figure A.1: Simulation Fit

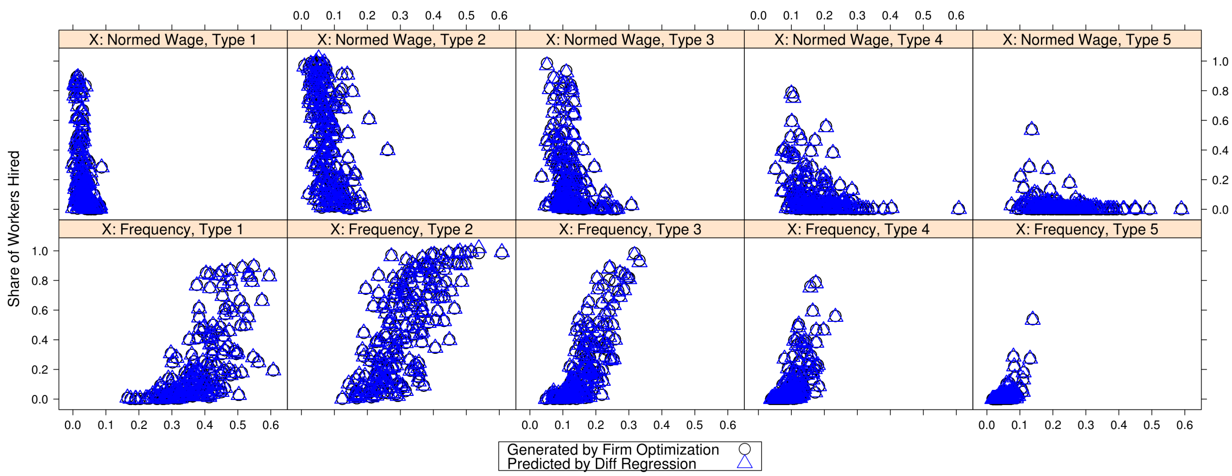


Table A.1: Simulation details

Variable	Description	Value
θ^T	Technological parameter.	2
k	Pareto shape parameter.	1.5
$\{\underline{m}_i\}$	Human capital shifters.	$\{4, 8, 12, 16, 20\}$
$\{w_{R,i}\}$	Regional wages by type.	$\sim$LogNormal $\mu = (12, 24, 36, 48, 60)$, $\sigma = 1/3$.
$\{a_{R,i}\}$	Regional type frequencies.	$\sim$LogNormal $\mu = (.4, .3, .15, .1, .05)$, $\sigma = 1/3$, scaled so that frequencies sum to one.
K, M	Firm capital and materials.	$\sim$LogNormal $\mu = 1$, $\sigma = 1$.
L	Level of L employed by firm.	Profit maximizing given K, M and region.
$\alpha_M, \alpha_K, \alpha_L$	Production Parameters.	$\alpha_M = 1/6$, $\alpha_K = 1/3$, $\alpha_L = 1/2$.
Control	Misc variable for output.	$\sim$LogNormal $\mu = 0$, $\sigma = 1$.
Coeff	Exponent on Control.	Control Coeff$= \pi$.
$\{\omega_j\}$	Firm idiosyncratic wage costs.	$\sim$LogNormal $\mu = 0$, $\sigma = .1$.

Sample: 200 regions with 20 firms per region, with errors $\sim$LogNormal($\mu = 0$, $\sigma = 1/2$).

Table A.2: Simulation Results

(a) Simulation First Stage Estimates: Technology and Human Capital

Variable	Parameter	Estimate	Std Err	Predicted
$\{\ln a_{R,i}\}$	$\left(\theta^T/\beta^T\right)$	3.912	.0019	4
$\{\ln w_{R,i}\}$	$\left(-k/\beta^T\right)$	-2.922	.0021	-3
Dummy (Type = 1)	$\left(\theta^T/\beta^T\right) k\left(\ln \underline{m}_1/\underline{m}_5\right)$	-9.376	.0057	-9.657
Dummy (Type = 2)	$\left(\theta^T/\beta^T\right) k\left(\ln \underline{m}_2/\underline{m}_5\right)$	-5.295	.0045	-5.498
Dummy (Type = 3)	$\left(\theta^T/\beta^T\right) k\left(\ln \underline{m}_3/\underline{m}_5\right)$	-2.950	.0031	-3.065
Dummy (Type = 4)	$\left(\theta^T/\beta^T\right) k\left(\ln \underline{m}_4/\underline{m}_5\right)$	-1.274	.0024	-1.339

(b) Simulation Second Stage Estimates: Production Parameters

Variable	Parameter	Estimate	Std Err	Predicted
$\ln M$	$\alpha_M/(1-\alpha_L)$	.3298	.0079	.3333
$\ln K$	$\alpha_K/(1-\alpha_L)$	.6680	.0080	.6667
$\ln c_{RT}$	$-\alpha_L/(1-\alpha_L)$	-.9303	.0748	-1
Control	Control Coeff	3.148	.0079	3.141

C Model Estimates: Baseline and Instrumental Variables

Table A.3: First Stage Estimates I

Industry	Beverage	Electrical Equip	Food	General Machines	Iron & Steel	Leather & Fur	Precision Equipment	Metal Products
	Dependent Variable: $\ln(\%\text{type})$							
$\ln(w_{R,i})$	-1.808^a	-2.977^a	-0.870	-2.687^a	-2.150^a	-0.708^c	-4.517^a	-3.174^a
$\ln(a_{R,i})$	1.673^a	1.878^a	1.489^a	1.794^a	1.018^a	0.636^a	3.358^a	1.439^a
m_1 (≤Junior HS: Fem)	-8.447^a	-9.491^a	-3.186	-10.170^a	7.190^a	-2.052	-13.450^a	-5.800^a
m_2 (≤Junior HS: Male)	-5.947^c	-7.181^a	-1.504	-6.171^a	12.370^a	-1.089	-11.160^a	-2.176^c
m_3 (Senior High School)	-2.470	-4.475^a	1.123	-3.180^a	14.210^a	-2.058^c	-4.100^b	-0.758
m_1*% Non-Ag Hukou	0.837	-7.619^a	-2.341^b	-5.957^a	-2.373^c	-4.544^a	-7.142^a	-6.038^a
m_2*% Non-Ag Hukou	0.306	-3.272^a	-1.880	-3.072^a	-1.355	-2.882^c	-3.957^c	-1.805^b
m_3*% Non-Ag Hukou	-1.102	-0.593	-0.837	-3.218^a	-2.394^a	-1.606^b	0.315	-1.104^b
m_4*% Non-Ag Hukou	-3.913	-4.572^a	-0.426	-7.026^a	10.130^a	-8.496^a	1.793	-2.491^b
$\underline{m}_1 *$ Urban Dummy	-0.271	-1.379^a	-1.462^a	-1.384^a	-1.393^a	-0.0822	-1.032^a	-1.408^a
$\underline{m}_2 *$ Urban Dummy	-0.007	-0.991^a	-1.085^a	-0.980^a	-0.585^a	-0.128	-1.176^a	-0.533^a
$\underline{m}_3 *$ Urban Dummy	0.286^c	0.139^b	0.175	0.427^a	0.503^a	0.220^c	-0.249	0.247^a
$\underline{m}_4 *$ Urban Dummy	2.212^a	1.513^a	1.743^a	2.336^a	3.275^a	0.683^a	1.053^a	2.147^a
m_1*% Foreign Equity	0.531^a	1.030^a	0.841^a	0.934^a	0.751^a	-0.107	1.952^a	0.876^a
m_2*% Foreign Equity	0.422^a	0.678^a	0.661^a	0.403^a	0.354^a	-0.0680	1.840^a	0.335^a
m_3*% Foreign Equity	0.106	0.259^a	0.197^b	0.143^a	0.083	0.257^a	0.574^a	0.145^a
m_4*% Foreign Equity	-0.005	0.232^a	0.015	0.351^a	-0.069	0.249	0.033	-0.150
$m_1 * \ln(\text{Firm Age})$	-2.803^a	-0.215	-0.983^a	-2.448^a	-2.160^a	0.113	0.727^b	-0.627^a
$m_2 * \ln(\text{Firm Age})$	-2.290^a	-0.547^a	-0.494^c	-1.864^a	-1.662^a	-0.190^b	0.319	-0.788^a
$m_3 * \ln(\text{Firm Age})$	0.714^a	-0.114	0.016	0.311^a	0.862^a	0.198	-0.510^b	0.417^a
$m_4 * \ln(\text{Firm Age})$	2.840^a	1.621^a	2.301^a	3.847^a	5.656^a	3.133^a	0.279	3.488^a
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,900	48,960	15,228	62,908	18,704	19,408	10,808	42,744
R-squared	0.124	0.117	0.098	0.139	0.168	0.208	0.246	0.124

Note: a, b and c denote 1, 5 and 10% significance level respectively.

Table A.4: First Stage Estimates II

Industry	Non-ferrous Metal	Other Non-metal	Paper	Plastic	PC & AV Equipment	Specific Machines	Textile	Wood
	Dependent Variable: $\ln(\%type)$							
$\ln(w_{R,i})$	-3.096^a	-1.693^a	-1.542^a	-3.324^a	-3.371^a	-1.260^a	-2.230^a	-1.220^b
$\ln(a_{R,i})$	1.627^a	1.664^a	0.332^b	1.321^a	2.785^a	1.961^a	0.830^a	2.286^a
m_1 ($\leq$Junior HS: Fem)	-1.189	-7.246^a	-3.469^c	-7.881^a	-13.770^a	-10.130^a	1.588	-10.890^a
m_2 ($\leq$Junior HS: Male)	3.768^c	-3.128^a	-0.645	-4.596^a	-11.970^a	-4.811^a	2.703^b	-9.086^a
m_3 (Senior High School)	6.119^a	-0.808	0.076	-2.657^b	-7.325^a	-1.515	3.468^a	-6.106^b
m_1*% Non-Ag Hukou	-4.591^a	-2.750^a	-6.210^a	-6.682^a	-7.176^a	-4.763^a	-6.271^a	-0.301
m_2*% Non-Ag Hukou	-0.370	-1.750^a	-6.148^a	-4.710^a	-5.210^a	-4.295^a	-5.555^a	-0.308
m_3*% Non-Ag Hukou	-0.903	-2.198^a	-3.251^a	-2.685^a	0.597	-1.463^a	-3.264^a	-2.549^a
m_4*% Non-Ag Hukou	3.403	-3.926^a	-7.690^a	-7.074^a	-3.291^a	-2.447	-4.025^a	-13.060^a
$\underline{m}_1 *$ Urban Dummy	-1.188^a	-1.333^a	-0.691^a	-1.057^a	-1.881^a	-1.597^a	-0.650^a	-1.630^a
$\underline{m}_2 *$ Urban Dummy	-0.601^a	-0.834^a	-0.338^b	-0.590^a	-1.619^a	-1.234^a	-0.421^a	-0.720^a
$\underline{m}_3 *$ Urban Dummy	0.108	0.250^a	0.350^a	0.272^a	-0.512^a	0.216^b	0.285^a	0.129
$\underline{m}_4 *$ Urban Dummy	1.791^a	2.570^a	2.644^a	2.413^a	0.902^a	1.924^a	2.709^a	3.331^a
m_1*% Foreign Equity	1.366^a	0.834^a	0.407^a	0.877^a	1.340^a	1.588^a	0.214^a	0.415^a
m_2*% Foreign Equity	0.432^a	0.244^a	0.153^c	0.361^a	1.072^a	0.750^a	0.202^a	0.176
m_3*% Foreign Equity	0.093	0.028	0.039	0.048	0.294^a	0.169^a	0.137^a	-0.142
m_4*% Foreign Equity	0.589^a	-0.310^a	-0.012	0.000	-0.160^b	0.097	0.442^a	0.197
$m_1 * \ln$(Firm Age)	-2.156^a	-1.016^a	-1.899^a	-0.857^a	0.310	-1.601^a	-0.384^a	-0.423
$m_2 * \ln$(Firm Age)	-1.838^a	-0.768^a	-0.819^a	-0.773^a	0.223	-1.675^a	-0.058	0.066
$m_3 * \ln$(Firm Age)	0.695^a	0.105	0.457^a	0.398^a	-0.049	0.100	0.445^a	-0.468
$m_4 * \ln$(Firm Age)	4.413^a	3.429^a	4.850^a	3.776^a	0.321^a	1.629^a	4.391^a	3.850^a
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,428	61,388	22,792	36,940	26,796	31,264	73,168	14,516
R-squared	0.145	0.150	0.164	0.130	0.188	0.177	0.221	0.245

Note: a, b and c denote 1, 5 and 10% significance level respectively.

Table A.5: First Stage IV Estimates I

Industry	Beverage	Electrical Equip	Food	General Machines	Iron & Steel	Leather & Fur	Precision Equipment	Metal Products
	Dependent Variable: $\ln(\%\text{type})$							
$\ln(w_{R,i})$	-1.721	-3.238[b]	-0.186	-2.891	-2.903[c]	-0.535	-3.198	-4.545[b]
$\ln(a_{R,i})$	1.456[a]	1.787[a]	1.507[a]	1.693[a]	0.737	0.622	1.112[b]	1.380[a]
m_1 (≤Junior HS: Fem)	-7.807	-9.325[b]	-1.710	-9.858	6.569	-2.042	-4.271	-2.848
m_2 (≤Junior HS: Male)	-5.249	-6.928[c]	-0.259	-5.764	12.11	-1.120	-0.555	2.663
m_3 (Senior High School)	-2.035	-4.301	2.302	-2.967	13.66	-2.081	0.447	4.791
m_1*% Non-Ag Hukou	0.101	-7.779[b]	-2.187	-6.158[b]	-3.391	-4.861	-7.066[b]	-5.198[c]
m_2*% Non-Ag Hukou	-0.453	-3.373	-1.690	-3.259	-2.213	-3.219	-2.760	-0.979
m_3*% Non-Ag Hukou	-1.375	-0.543	-0.704	-3.145	-2.582	-1.759	-1.182	-0.950
m_4*% Non-Ag Hukou	-3.923	-4.320	0.774	-6.701	9.228	-8.741	-1.589	2.029
$\underline{m}_1 *$ Urban Dummy	-0.299	-1.401[a]	-1.439[a]	-1.399[a]	-1.384[a]	-0.0781	-1.430[a]	-1.233[a]
$\underline{m}_2 *$ Urban Dummy	-0.0368	-1.012[a]	-1.057[a]	-0.994[a]	-0.608[b]	-0.124	-0.560[b]	-0.646[b]
$\underline{m}_3 *$ Urban Dummy	0.327	0.139	0.176	0.431[a]	0.500[b]	0.214	0.244	0.112
$\underline{m}_4 *$ Urban Dummy	2.204[a]	1.545[a]	1.613[a]	2.347[a]	3.310[a]	0.673	2.175[a]	1.910[a]
m_1*% Foreign Equity	0.526[a]	1.029[a]	0.854[a]	0.928[a]	0.739[a]	-0.106	0.868[a]	1.342[a]
m_2*% Foreign Equity	0.417[a]	0.678[a]	0.675[a]	0.397[a]	0.330[a]	-0.0662	0.333[a]	0.397[a]
m_3*% Foreign Equity	0.103	0.254[a]	0.205[b]	0.151[a]	0.0786	0.249[b]	0.147[c]	0.0882
m_4*% Foreign Equity	0.0120	0.224[b]	-0.0120	0.340[a]	-0.00873	0.243	-0.150	0.664[a]
$m_1 * \ln(\text{Firm Age})$	-2.860[a]	-0.225	-0.957[a]	-2.471[a]	-2.191[a]	0.109	-0.650[c]	-2.216[a]
$m_2 * \ln(\text{Firm Age})$	-2.342[a]	-0.582[b]	-0.451	-1.904[a]	-1.764[a]	-0.186	-0.842[a]	-1.982[a]
$m_3 * \ln(\text{Firm Age})$	0.758[a]	-0.110	0.0237	0.324	0.851[a]	0.194	0.431[c]	0.670[b]
$m_4 * \ln(\text{Firm Age})$	2.897[a]	1.658[a]	2.325[a]	3.888[a]	5.806[a]	3.139[a]	3.539[a]	4.715[a]
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,783	48,750	15,087	62,563	18,600	19,366	42,639	14,257
R-squared	0.124	0.118	0.097	0.139	0.168	0.208	0.123	0.146

Note: a, b and c denote 1, 5 and 10% significance level respectively.

Table A.6: First Stage IV Estimates II

Industry	Non-ferrous Metal	Other Non-metal	Paper	Plastic	PC & AV Equipment	Specific Machines	Textile	Wood
				Dependent Variable: $\ln(\%\text{type})$				
$\ln(w_{R,i})$	-2.137	-1.008	-3.339	-3.621	-2.965	-1.469	-1.984	-2.190
$\ln(a_{R,i})$	1.586^a	0.0881	2.669^a	1.335^b	2.869^b	2.074^b	0.632	2.004^b
m_1 ($\leq$Junior HS: Fem)	-7.588	-2.266	-13.16^a	-7.977	-9.795	-10.54^a	2.482	-7.942
m_2 ($\leq$Junior HS: Male)	-3.320	0.475	-11.35^b	-4.611	-7.848	-5.203	3.580	-5.772
m_3 (Senior High School)	-1.036	0.839	-6.854^c	-2.649	-1.729	-1.735	4.063	-3.304
$m_1*\%$ Non-Ag Hukou	-2.898^c	-7.227^c	-7.501	-6.344^b	-9.315^c	-4.400	-7.153^c	-0.925
$m_2*\%$ Non-Ag Hukou	-1.808	-7.175	-5.441	-4.350	-5.861	-3.927	-6.481	-0.640
$m_3*\%$ Non-Ag Hukou	-2.212	-3.458	0.609	-2.521	0.253	-1.432	-3.468	-2.300
$m_4*\%$ Non-Ag Hukou	-4.097	-7.538	-2.892	-6.724	2.990	-2.423	-3.940	-9.706
$\underline{m}_1 *$ Urban Dummy	-1.351^a	-0.705^a	-1.903^a	-1.063^a	-1.064^a	-1.587^a	-0.652^a	-1.622^a
$\underline{m}_2 *$ Urban Dummy	-0.855^a	-0.355^c	-1.638^a	-0.595^b	-1.177^a	-1.227^a	-0.424^b	-0.707^b
$\underline{m}_3 *$ Urban Dummy	0.247^c	0.344	-0.503	0.277	-0.224	0.220	0.294^b	0.206
$\underline{m}_4 *$ Urban Dummy	2.583^a	2.677^a	0.936^a	2.404^a	1.061^b	1.874^a	2.695^a	3.095^a
$m_1*\%$ Foreign Equity	0.829^a	0.405^a	1.340^a	0.875^a	1.945^a	1.588^a	0.207^a	0.412^a
$m_2*\%$ Foreign Equity	0.243^a	0.155^c	1.074^a	0.357^a	1.840^a	0.749^a	0.198^a	0.153
$m_3*\%$ Foreign Equity	0.0265	0.0430	0.296^b	0.0468	0.575^a	0.167^b	0.136^b	-0.128
$m_4*\%$ Foreign Equity	-0.312^b	-0.0326	-0.167	-0.0189	0.0393	0.108	0.472^a	0.371
$m_1 * \ln(\text{Firm Age})$	-1.024^a	-1.910^a	0.312	-0.854^a	0.715	-1.590^b	-0.387^b	-0.429
$m_2 * \ln(\text{Firm Age})$	-0.803^a	-0.817^b	0.216	-0.790^a	0.341	-1.670^a	-0.0606	0.0192
$m_3 * \ln(\text{Firm Age})$	0.106	0.467	-0.0426	0.400	-0.461	0.0970	0.454^a	-0.379
$m_4 * \ln(\text{Firm Age})$	3.503^a	4.848^a	0.326	3.793^a	0.220	1.637^a	4.404^a	3.781^a
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,946	22,667	26,761	36,816	10,808	31,078	72,828	14,126
R-squared	0.150	0.164	0.188	0.129	0.246	0.178	0.219	0.212

Note: a, b and c denote 1, 5 and 10% significance level respectively.

Table A.7: Hiring Model Primitive IV Estimates

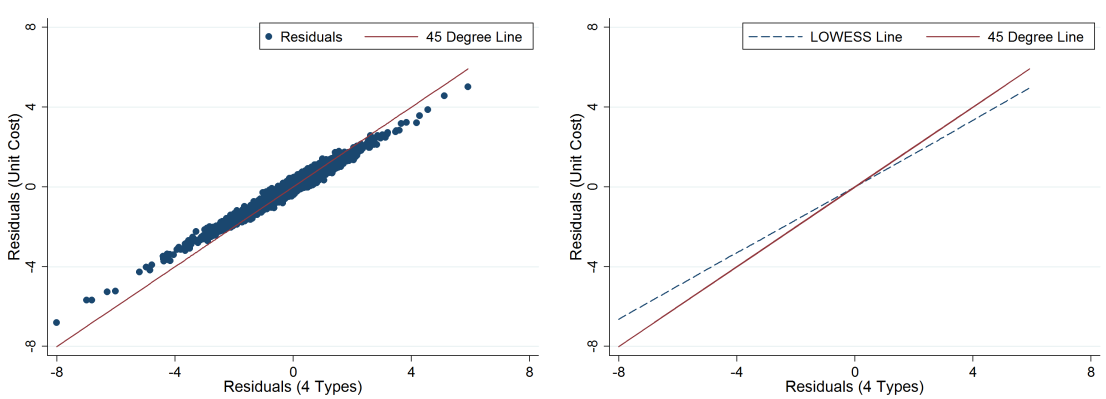
Industry	k	θ	Industry	k	θ
Beverage	2.18 (.55)	1.16 (.11)	Non-ferrous Metal	2.35 (.20)	1.19 (.03)
Electrical	2.84 (.20)	1.18 (.03)	Non-metal Products	17.0 (5.2)	0.51 (.29)
Food	1.10 (.51)	1.39 (1.1)	Paper	2.24 (.16)	1.39 (.04)
General Machines	2.72 (.17)	1.18 (.03)	Plastic	3.69 (.33)	1.07 (.03)
Iron & Steel	6.01 (2.8)	0.91 (.07)	PC & AV	2.05 (.22)	1.48 (.09)
Leather & Fur	1.92 (.73)	0.73 (.18)	Specific Machines	1.70 (.19)	1.44 (.08)
Precision Tools	3.93 (.44)	1.02 (.03)	Textile	4.21 (.65)	0.88 (.04)
Metal Products	4.25 (.63)	1.07 (.05)	Wood	2.06 (.3)	1.33 (.09)

Bootstrapped Standard Errors reported in parentheses.

C.1 Residual Comparison: Unit Labor Costs vs Substitutable Labor

Of particular interest for work on productivity are the residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity. Figure A.1 contrasts unexplained productivity (estimation residuals) when unit labor costs are used with estimates that measure labor by including the employment of each worker type. Examining the 45 degree line also plotted in the Figure, a general pattern emerges: above average firms under the employment measure are slightly less productive under the unit cost approach, while below average firms are more productive. This suggests that a more detailed analysis of the role of local factor markets may substantially alter interpretation of differences in firm productivity.

Figure A.1: Productivity: Unit Labor Costs vs Total Employment (General Machines)



C.2 Comparison with Conventional Labor Measures

The estimates above reflect a procedure using regional variation to recover the unit cost of labor. Often, such information is not incorporated into production estimation. Instead, the number of employees or total wage bill are used to capture the effective labor available to a firm. The mean of the second stage estimates using these labor measures are contrasted with unit cost method in Table A.8 (full results in Table A.19 of the Supplemental Appendix). The production coefficients using the total wage bill or total employment are very similar, reflecting the high correlation of these variables. However, both measures mask regional differences in factor markets. Once local substitution patterns are taken into account explicitly, substantial differences emerge.[55] Most notably, the capital share tends to be higher under the approach of this paper, while the labor share is substantially lower.

Table A.8: Second Stage Estimates vs Homogeneous Labor Estimates

	Unit Labor Cost			Total Wage Bill			Total Employment		
	α_L	α_K	α_M	α_L	α_K	α_M	α_L	α_K	α_M
Average	0.18	0.16	0.48	0.28	0.09	0.56	0.28	0.09	0.58

Pushing this comparison further, Table A.9 predicts the propensity to export of firms by residual firm productivity. The first column shows the results under the unit cost method. The second and third columns show the results when labor is measured as perfectly substitutable (either by employment of each type or wages). Note that in all cases, regional and industry effects are controlled for. The Table illustrates that productivity estimates which account for regional factor markets are almost twice as important in predicting exports as the other measures. Section H.4 of the Appendix shows that similar results hold when examining sales growth and three year survival rate: productivity under the unit cost approach is more important in predicting firm performance, suggesting the other measures conflate the role of advantageous factor markets with productivity.

Table A.9: Explaining Propensity to Export with Productivity

	Export Dummy (2005)		
Productivity under Unit Cost method	0.0260***		
	(0.00430)		
Productivity under L = 4 Types		0.0140***	
		(0.00248)	
Productivity under L = Wage Bill			0.0177***
			(0.00262)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	127,082	127,082	127,082
R-squared	0.204	0.204	0.204

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

[55] The residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity, are compared in Appendix C.1.

D Robustness Checks: Firm Size and Input Complementarity

Table A.10: Firm Size and Complementarity Controls

	Baseline		Type*ln (Emp)		Type*ln (K/Emp) & Type*ln (M/Emp)	
Industry	k	θ	k	θ	k	θ
Beverage	2.12 (.38)	1.24 (.08)	2.09 (.39)	1.24 (.09)	2.11 (.41)	1.22 (.10)
Electrical	2.60 (.15)	1.22 (.02)	2.57 (.15)	1.22 (.02)	2.47 (.16)	1.23 (.03)
Food	1.59 (.36)	1.28 (.13)	1.57 (.36)	1.27 (.15)	1.60 (.38)	1.25 (.16)
General Machines	2.50 (.14)	1.22 (.03)	2.41 (.14)	1.23 (.03)	2.52 (.17)	1.21 (.04)
Iron & Steel	3.21 (.56)	1.00 (.06)	3.16 (.41)	1.07 (.09)	3.16 (.44)	1.02 (.08)
Leather & Fur	2.15 (.70)	0.76 (.14)	2.36 (.69)	0.82 (.11)	2.09 (.72)	0.78 (.10)
Metal Products	3.20 (.24)	1.10 (.03)	3.12 (.23)	1.11 (.03)	3.18 (.25)	1.07 (.04)
Non-ferrous Metal	2.89 (.38)	1.15 (.05)	2.66 (.35)	1.19 (.06)	2.79 (.33)	1.17 (.07)
Non-metal Products	2.02 (.16)	1.25 (.04)	1.98 (.16)	1.28 (.04)	2.08 (.17)	1.21 (.05)
Paper	6.25 (3.8)	0.73 (.11)	5.89 (1.6)	0.71 (.15)	6.13 (1.8)	0.74 (.16)
PC & AV	2.21 (.14)	1.41 (.04)	2.19 (.14)	1.41 (.04)	2.19 (.15)	1.42 (.06)
Plastic	3.51 (.29)	1.08 (.03)	3.41 (.29)	1.08 (.03)	3.57 (.25)	1.06 (.04)
Precision Tools	2.34 (.18)	1.43 (.05)	2.41 (.19)	1.38 (.05)	2.39 (.22)	1.41 (.05)
Specific Machines	1.63 (.18)	1.43 (.07)	1.69 (.18)	1.37 (.06)	1.67 (.19)	1.39 (.07)
Textile	3.73 (.36)	0.95 (.03)	3.59 (.26)	0.97 (.03)	3.65 (.27)	0.98 (.05)
Wood	1.52 (.22)	1.62 (.17)	1.44 (.21)	1.67 (.21)	1.48 (.20)	1.59 (.19)

Bootstrapped standard errors reported in parentheses.

E Robustness: Unobserved Regional Heterogeneity

Table A.11: Prefecture-Industry Level Instruments Using Prefecture Averages of Unit Labor Costs and Materials

	Baseline			Instruments		
Industry	α_L	α_K	α_M	α_L	α_K	α_M
Beverage	.18 (.04)	.13 (.01)	.62 (.04)	.20 (.06)	.12 (.03)	.64 (.06)
Electrical	.17 (.01)	.19 (.01)	.42 (.01)	.16 (.03)	.20 (.02)	.45 (.03)
Food	.15 (.06)	.11 (.01)	.65 (.06)	.14 (.07)	.13 (.02)	.60 (.08)
General Machines	.17 (.02)	.14 (.01)	.55 (.01)	.21 (.05)	.12 (.03)	.59 (.04)
Iron & Steel	.48 (.05)	.09 (.01)	.36 (.04)	.52 (.08)	.09 (.02)	.38 (.06)
Leather & Fur	.07 (.05)	.18 (.02)	.53 (.06)	.06 (.05)	.18 (.04)	.57 (.07)
Metal Products	.31 (.05)	.13 (.01)	.40 (.02)	.30 (.03)	.13 (.03)	.48 (.05)
Non-ferrous Metal	.17 (.02)	.10 (.01)	.58 (.01)	.14 (.10)	.12 (.02)	.59 (.06)
Non-metal Products	.14 (.08)	.19 (.04)	.45 (.05)	.12 (.05)	.18 (.02)	.46 (.04)
Paper	.09 (.02)	.25 (.01)	.41 (.01)	.09 (.03)	.22 (.05)	.45 (.07)
PC & AV	.15 (.01)	.19 (.01)	.39 (.01)	.16 (.03)	.17 (.02)	.38 (.03)
Plastic	.22 (.03)	.17 (.01)	.36 (.02)	.22 (.04)	.14 (.02)	.42 (.04)
Precision Tools	.17 (.01)	.18 (.01)	.44 (.01)	.21 (.06)	.15 (.03)	.43 (.05)
Specific Machines	.12 (.02)	.20 (.01)	.43 (.01)	.14 (.04)	.19 (.03)	.49 (.03)
Textile	.01 (.04)	.14 (.01)	.59 (.03)	.01 (.05)	.16 (.02)	.55 (.05)
Wood	.20 (.15)	.14 (.03)	.49 (.07)	.23 (.16)	.15 (.04)	.48 (.10)

Bootstrapped standard errors reported in parentheses.

F WTO Accession Counterfactual Graphs

Figure A.1: Predicted Type Share Changes By Prefecture Due to WTO Accession

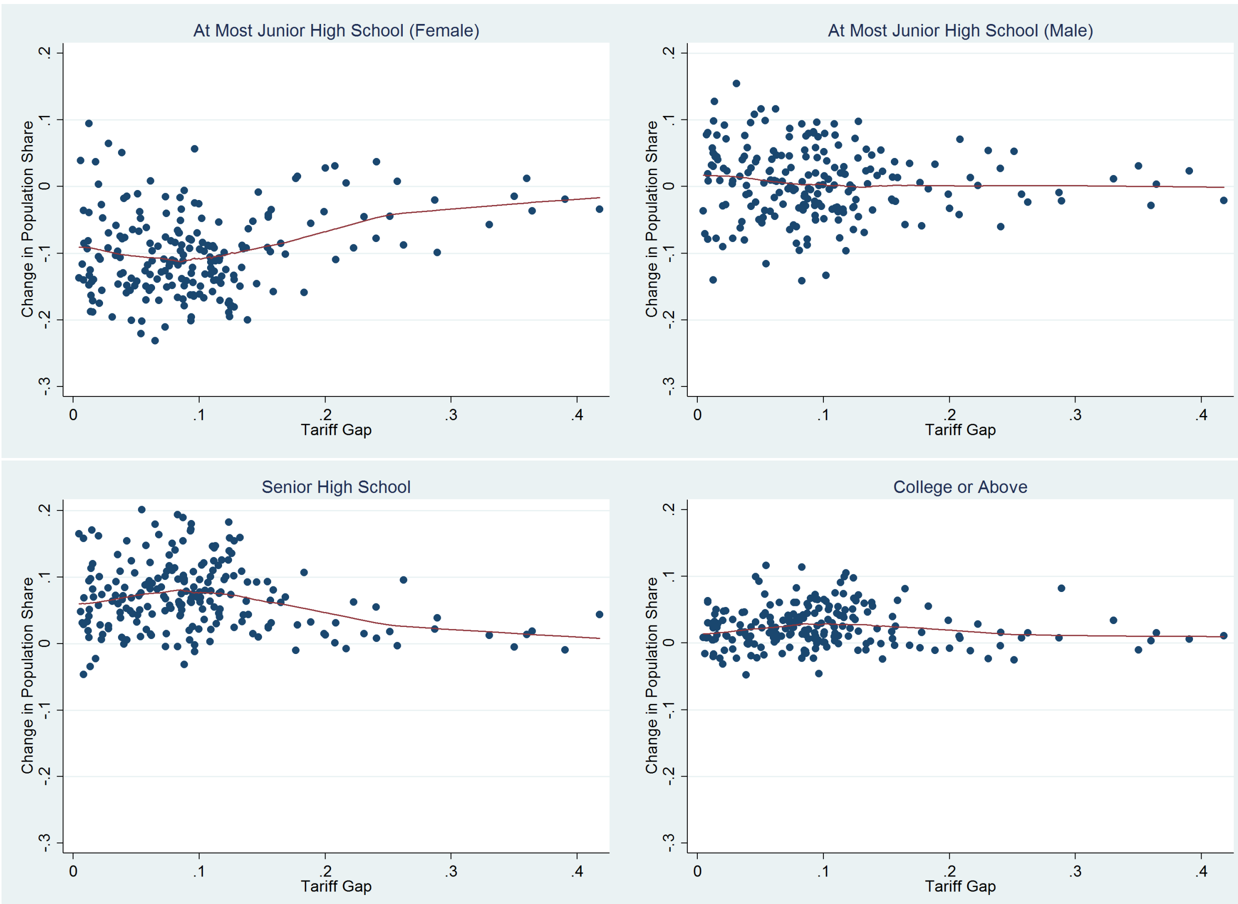


Table A.12: Intraindustry Unit Labor Cost Ratios: Baseline vs No WTO Accession

Industry	Baseline c_R^T $^{75}/_{25}$	No Accession c_R^T $^{75}/_{25}$	Industry	Baseline c_R^T $^{75}/_{25}$	No Accession c_R^T $^{75}/_{25}$
Beverage	1.51	1.52	Non-metal Products	1.42	1.42
Electrical	1.38	1.37	Paper	1.66	1.68
Food	1.81	1.83	PC & AV	1.44	1.44
General Machines	1.41	1.40	Plastic	1.35	1.35
Iron & Steel	1.34	1.32	Precision Tools	1.80	1.80
Leather & Fur	1.92	1.95	Specific Machines	1.99	1.99
Metal Products	1.33	1.32	Textile	1.37	1.37
Non-ferrous Metal	1.45	1.43	Wood	1.47	1.48

G Supplemental Derivations

G.1 Derivation of Region-Technology Budget Shares

The expressions which fix the cutoff cost draw $\overline{\eta}_R^T$ and mass of entry $\mathbb{M}_R^T$ can be neatly summarized by defining the mass of entrants who produce, $\widetilde{\mathbb{M}}_R^T$, and the (locally weighted) average cost draw in each region, $\widetilde{\eta}_R^T$:

$$\widetilde{\mathbb{M}}_R^T \equiv \mathbb{M}_R^T G\left(\overline{\eta}_R^T\right), \qquad \widetilde{\eta}_R^T \equiv \int_0^{\overline{\eta}_R^T} \left(\eta_z^T u_R^T \left(U_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} dG(z)/G\left(\overline{\eta}_R^T\right).$$

Using the profit maximizing price P_{Rj}^T and combining Equations (2.9) and (3.1) then yields the equilibrium quantity produced,

$$Q_{Rj}^T = \rho \mathbb{I}\left(u_R^T \eta_j \left(U_R^T/\sigma_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} / u_R^T \eta_j \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{G.1}$$

Aggregating revenues using Equation (G.1) shows that each consumer's budget share allocated to region R and industry T is

$$\text{Consumer Budget Share for R, T:} \quad \left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{G.2}$$

Consequently, since free entry implies expected profits must equal expected fixed costs, the mass of entrants $\mathbb{M}_R^T$ solves the implicit form[56]

$$(1-\rho)\mathbb{I}\left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t\right) = \mathbb{M}_R^T u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e\right), \tag{G.3}$$

while the equilibrium cost cutoffs $\overline{\eta}_R^T$ solve the zero profit condition[57]

$$(1-\rho)\mathbb{I}\left(\sigma_R^T\right)^{1/(1-\rho)} \left(u_R^T \overline{\eta}_R^T \left(U_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} = u_R^T f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{G.4}$$

[56]To see a solution exists, note that for fixed prices, $\{\widetilde{\eta}_R^T\}$, and $\{\overline{\eta}_R^T\}$, necessarily $\mathbb{M}_R^T \in A_R^T \equiv \left[0, (1-\rho)\mathbb{I}/u_R^T F_e\right]$. Existence follows from the Brouwer fixed point theorem on the domain $\times_{R,T} A_R^T$ for $H\left(\left\{\widetilde{\mathbb{M}}_R^T\right\}\right) \equiv (1-\rho)\mathbb{I}\left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t\right) / u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e\right)$.

[57]To see a solution exists, note that for fixed prices, $\left\{\mathbb{M}_{R'}^{T'}\right\}$ and $\{U_R^T\}$, the LHS ranges from 0 to ∞ as $\overline{\eta}_R^T$ varies, while the RHS is bounded away from 0 and ∞ when $\min\left\{\widetilde{\eta}_r^t G\left(\overline{\eta}_r^t\right)\right\} > 0$. $\widetilde{\eta}_R^T G\left(\overline{\eta}_R^T\right) > 0$ follows from inada type conditions on goods from each T and R.

Equations (G.3) and (G.4) fix $\overline{\eta}_R^T$ since combining them shows

$$\int_0^{\overline{\eta}_R^T} \left(\eta_z^T/\overline{\eta}_R^T\right)^{\rho/(\rho-1)} dG(z)/G\left(\overline{\eta}_R^T\right) = 1 + F_e/f_e G\left(\overline{\eta}_R^T\right).$$

In particular, $\overline{\eta}_R^T$ does not vary by region or technology. Thus, Equation (G.4) shows that

$$U_R^T u_R^T/\sigma_R^T = \left[(1-\rho)\mathbb{I}/f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t\right]^{1-\rho} / \left(\overline{\eta}_R^T\right)^{\rho}. \tag{G.5}$$

where the RHS does not vary by region or technology. Combining this equation with (3.1) shows $Q_{Rj}^T = Q_{R'j}^{T'}$ for all (T,R) and (T',R'), so that $\mathbb{M}_R^T u_R^T/\sigma_R^T = \mathbb{M}_{R'}^{T'} u_{R'}^{T'}/\sigma_{R'}^{T'}$. At the same time, using Equation (G.5) reduces (G.2) to

$$\text{Consumer Budget Share for R, T:} \quad \mathbb{M}_R^T u_R^T / \sum_{t,r} \mathbb{M}_r^t u_r^t = \sigma_R^T / \sum_{t,r} \sigma_r^t = \sigma_R^T.$$

Since $\sum_{t,r} \sigma_r^t = 1$, each region and industry receive a share σ_R^T of consumer expenditure.

G.2 Regional Variation in Input Use

Equation (4.1) specifies the relative shares of each type of worker hired. Since input markets are competitive, firms and workers take regional labor market characteristics as given. As characteristics such as wages worker availability and human capital vary, the share of each labor type hired differs across regions. These differences can be broken up into direct and indirect effects. Direct effects ignore substitution by holding the unit labor cost $\widetilde{c}_{RT}$ constant, while indirect effects measure how regional differences give rise to substitution. The direct effects are easy to read off of Equation (4.1), showing:

$$\text{Direct Effects:} \quad d\ln s_{R,T,i}/d\ln w_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = -k/\beta^T \ < 0, \tag{G.6}$$

$$d\ln s_{R,T,i}/d\ln a_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = \theta^T/\beta^T \ > 0, \tag{G.7}$$

$$d\ln s_{R,T,i}/d\ln \underline{m}_i^T|_{\widetilde{c}_{RT}\text{ constant}} = k\theta^T/\beta^T > 0. \tag{G.8}$$

These direct effects have the obvious signs: higher wages ($w_{R,i}\uparrow$) discourage hiring a particular type while greater availability ($a_{R,i}\uparrow$) and higher human capital ($m_{T,i}\uparrow$) encourage hiring that type.

The indirect effects of substitution through $\widetilde{c}_{RT}$ are less obvious as seen by

$$d\ln\widetilde{c}_{RT}^{k}/d\ln w_{R,i} = \left(k/\theta^{T}\right)\left[a_{R,i}\left(\underline{m}_{i}^{T}\right)^{k} w_{R,i}^{1-k-\beta^{T}/\theta^{T}}\right]^{\theta^{T}/\beta^{T}} \widetilde{c}_{RT}^{k\left(\theta^{T}/\beta^{T}\right)} > 0, \tag{G.9}$$

$$d\ln\widetilde{c}_{RT}^{k}/d\ln a_{R,i} = -\left[a_{R,i}\left(\underline{m}_{i}^{T}\right)^{k} w_{R,i}^{1-k-\beta^{T}/\theta^{T}}\right]^{\theta^{T}/\beta^{T}} \widetilde{c}_{RT}^{k\left(\theta^{T}/\beta^{T}\right)} < 0, \tag{G.10}$$

$$d\ln\widetilde{c}_{RT}^{k}/d\ln \underline{m}_{i}^{T} = -k\left[a_{R,i}\left(\underline{m}_{i}^{T}\right)^{k} w_{R,i}^{1-k-\beta^{T}/\theta^{T}}\right]^{\theta^{T}/\beta^{T}} \widetilde{c}_{RT}^{k\left(\theta^{T}/\beta^{T}\right)} < 0. \tag{G.11}$$

Thus, the indirect effects counteract the direct effects through substitution. To see the total of the direct and indirect effects, define the Type-Region-Technology coefficients $\chi_{i,R,T}$:

$$\chi_{i,R,T} \equiv 1-\left[a_{R,i}\left(\underline{m}_{i}^{T}\right)^{k} w_{R,i}^{1-k-\beta^{T}/\theta^{T}}\right]^{\theta^{T}/\beta^{T}} \widetilde{c}_{RT}^{k\left(\theta^{T}/\beta^{T}\right)}.$$

Investigation shows that each $\chi_{i,R,T}$ is between zero and one. Combining Equations (G.6-G.8) and Equations (G.9-G.11) shows that the direct effect dominates since

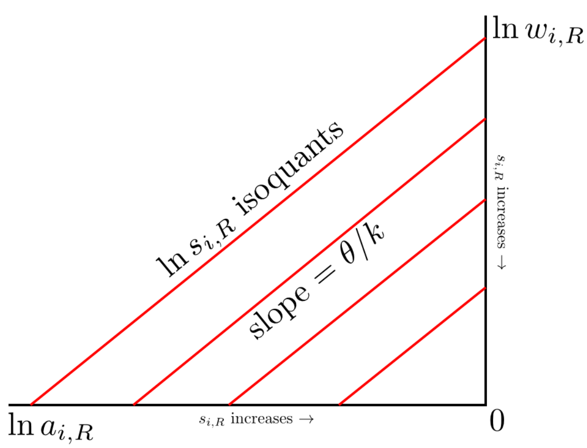
$$\text{Total Effects}: \quad d\ln s_{R,T,i}/d\ln w_{R,i} = \left[-k/\beta^{T}\right]\chi_{i,R,T} < 0, \tag{G.12}$$

$$d\ln s_{R,T,i}/d\ln a_{R,i} = \left[\theta^{T}/\beta^{T}\right]\chi_{i,R,T} > 0, \tag{G.13}$$

$$d\ln s_{R,T,i}/d\ln \underline{m}_{i}^{T} = \left[k\theta^{T}/\beta^{T}\right]\chi_{i,R,T} > 0. \tag{G.14}$$

Equations (G.12-G.14) summarize the relationship between regions and labor market characteristics. For small changes in labor market characteristics, the log share of a type hired in linear in log characteristics with a slope determined by model parameters and a regional shifter $\chi_{i,R,T}$. These (local) isoquants for the share of type i workers hired in region R are depicted in Figure A.1.

Figure A.1: Local isoquants for Share of Workers Hired



G.3 Regional Variation in Theory: Isoquants

Equations (G.12-G.14) also characterize local isoquants of hiring the same share of a type across regions. It is immediate that for small changes in market characteristics, $\begin{pmatrix} \Delta_w, & \Delta_a, & \Delta_m \end{pmatrix}$, the share of a type hired is constant so long as

$$-\left(k/\theta^T\right)\Delta_w/w_{R,i}+\Delta_a/a_{R,i}+k\Delta_m/\underline{m}_i^T=0.$$

For instance, firms in regions R and R' will hire the same fraction of type i workers for small differences in characteristics (Δ_w,Δ_a) so long as

$$\Delta_w/\Delta_a=\left(\theta^T/k\right)w_{R,i}/a_{R,i}. \tag{G.15}$$

By itself, an increase in type i wages Δ_w would cause firms to hire a lower share of type i workers as indicated by the direct effect. However, Equation (G.15) shows that firms would keep the same share of type i workers if the availability Δ_a increases concurrently so that Equation (G.15) holds.

G.4 Derivation of Unit Labor Costs

Local trade offs and the dependence on the regional labor supply characteristics a_R and w_R is made explicit by considering the technology and region specific cost function $C^T\left(H|a_R,w_R\right)$, defined by

$$C^T\equiv\min_{N,\underline{h}}N\left[\sum_i a_{R,i}w_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)+fc_R^T\right]\text{ where }H_i=Na_{R,i}\underline{m}_i^T\int_{\underline{h}_i}^{\infty}hd\Psi\quad\forall i. \tag{G.16}$$

Here Ψ denotes the CDF of match quality. Letting μ_i denote the Lagrange multiplier for each of the $\mathbb{S}$ cost minimization constraints, the first order conditions for $\{\underline{h}_i\}$ imply $\mu_i=w_{R,i}/\underline{m}_i^T\underline{h}_i$, while the choice of N implies

$$C^T\left(H|a_R,w_R\right)=\sum_i\mu_iH_i=N\sum w_{R,i}a_{R,i}\int_{\underline{h}_i}^{\infty}h/\underline{h}_id\Psi. \tag{G.17}$$

Equation (G.17) shows that the multipliers μ_i are the marginal cost contribution per skill unit to H_i of the last type i worker hired. The cost function C^T implies the unit labor cost of L in region R is

$$\text{Unit Labor Cost Problem}:\quad c_R^T\equiv\min_H C^T\left(H|a_R,w_R\right)\text{ subject to }L=1. \tag{G.18}$$

Under the parameterization $\Psi(h) = 1 - h^{-k}$, Equations (2.1) become

$$H_i = a_{R,i} k / (k-1) \cdot \underline{m}_i^T \underline{h}_i^{1-k} \cdot N. \tag{G.19}$$

From the FOCs above, $w_{R,i} H_i / \underline{m}_i^T \underline{h}_i C_T(H|a_R, w_R) = H_i^{\theta^T} / \sum_j H_j^{\theta^T}$, and $L = 1 = \left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T}$ so

$$\underline{h}_i = w_{R,i} H_i^{1-\theta^T} / \underline{m}_i^T C_T(H|a_R, w_R). \tag{G.20}$$

Substitution now yields

$$H_i = a_{R,i} k / (k-1) \cdot \underline{m}_i^T \left(w_{R,i} H_i^{1-\theta^T} / \underline{m}_i^T C_T(H|a_R, w_R) \right)^{1-k} \cdot N. \tag{G.21}$$

Further reduction and the definition of β^T shows that

$$H_i^{\beta^T} = H_i^{\theta^T + k - k\theta^T} = a_{R,i} k / (k-1) \cdot \left(\underline{m}_i^T\right)^k w_{R,i}^{1-k} C_T(H|a_R, w_R)^{k-1} N. \tag{G.22}$$

Again using $\left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T} = 1$ then shows

$$1 = \sum_i \left[a_{R,i} k / (k-1) \cdot \underline{m}_i^{Tk} w_{R,i}^{1-k} \left(c_R^T\right)^{k-1} N \right]^{\theta^T / \beta^T}. \tag{G.23}$$

From the definition of the cost function we have (substituting in G.20)

$$c_R^T = N \left[\sum_i a_{R,i} w_{R,i} \underline{h}_i^{-k} + f c_R^T \right] = \sum_i w_{R,i} \left((k-1) / k \right) H_i / \underline{m}_i^T \underline{h}_i + N f c_R^T.$$

Therefore from $w_{R,i} H_i / \underline{m}_i^T \underline{h}_i C_T(H|a_R, w_R) = H_i^{\theta^T}$ it follows

$$1 = \sum_i (k-1) / k \cdot H_i^{\theta^T} + N f = (k-1) / k + N f,$$

and therefore $N = 1 / fk$. Now from Equation (G.23), c_R^T is seen to be Equation (2.4).

G.5 Derivation of Employment Shares

Combining Equations (G.20), (G.22) and $N = 1/fk$ shows

$$\underline{h}_i = a_{R,i}^{(1-\theta^T)/\beta^T} \left(\underline{m}_i^T\right)^{-\theta^T/\beta^T} w_{R,i}^{1/\beta^T} \left(c_R^T\right)^{-1/\beta^T} / \left(f(k-1)\right)^{(1-\theta^T)/\beta^T}. \tag{G.24}$$

Let $A^T_{R,i}$ be the number of type i workers hired to make $L=1$, exclusive of fixed search costs. By definition, $A^T_{R,i} = N|_{L=1} \cdot a_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right) = a_{R,i}\underline{h}_i^{-k}/fk$. Using Equation (G.24),

$$A^T_{R,i} = k^{-1}(k-1)\, a_{R,i}^{\theta^T/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(c_R^T\right)^{k/\beta^T} \left((k-1)f\right)^{-\theta^T/\beta^T}.$$

Labor is also consumed by the fixed search costs which consist of $N|_{L=1} \cdot f = 1/k$ labor units. Therefore, if $\widetilde{A}^T_{R,i}$ denotes the total number of type i workers hired to make $L=1$, necessarily $\widetilde{A}^T_{R,i} = A^T_{R,i} + \widetilde{A}^T_{R,i}/k$ so $\widetilde{A}^T_{R,i} = k(k-1)^{-1} A^T_{R,i}$, and the total number of type i workers hired in region R using technology T is $L^T_R \widetilde{A}^T_{R,i}$. The total number of employees in R, T is $\sum_i L^T_R \widetilde{A}^T_{R,i} = L^T_R \left(c^T_R\right)^{k/\beta^T} \left(\widetilde{c}^T_R\right)^{(1-k)\theta^T/\beta^T}$, where $\widetilde{c}^T_R$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$[58].

G.6 Derivation of Indirect Utility

First, note that within an industry T and region R, the quantity a firm j produces relative to quantity $\overline{Q}^T_R$ that the highest cost firm produces is $Q^T_{Rj}/Q^T_{R\bar{j}} = \left(\overline{\eta}^T_R/\eta_j\right)^{1/(1-\rho)}$. From the condition that the highest cost firm makes zero profits, $\overline{Q}^T_R = \rho f_e/(1-\rho)\,\overline{\eta}^T_R$, and consequently

$$Q^T_{Rj} = \rho f_e \left(\overline{\eta}^T_R\right)^{\rho/(1-\rho)} / (1-\rho)\left(\eta_j\right)^{1/(1-\rho)}.$$

Since the share of income spent on industry T and region R, $\sigma^T_R \mathbb{I}$, must equal total costs,

$$\sigma^T_R \mathbb{I} = u^T_R \mathbb{M}^T_R \left[\int_0^{\overline{\eta}^T_R} \rho f_e \left(\overline{\eta}^T_R\right)^{\rho/(1-\rho)} / (1-\rho)\left(\eta_j\right)^{1/(1-\rho)} + f_e dG(j) + F_e\right].$$

Free entry and constant markups also implies that entry costs $u^T_R F_e$ must equal expected profits, so

$$u^T_R \left[\int_0^{\overline{\eta}^T_R} f_e \left(\overline{\eta}^T_R\right)^{\rho/(1-\rho)} / \left(\eta_j\right)^{1/(1-\rho)} - f_e dG(j)\right] = u^T_R F_e.$$

Combining these expressions shows

$$\mathbb{M}^T_R = \sigma^T_R \mathbb{I}/u^T_R \left[\int_0^{\overline{\eta}^T_R} f_e \left(\overline{\eta}^T_R\right)^{\rho/(1-\rho)} / (1-\rho)\left(\eta_j\right)^{1/(1-\rho)} dG(j)\right].$$

[58]Formally $\tilde{c}^T_R \equiv \min_H C_T\left(H|a_R, \left\{w_{R,i}^{-k/\theta^T(1-k)}\right\}\right)$ subject to $L=1$.

Finally, expanding the expression for welfare (say, W) and using $\sum_{T,R} \sigma_R^T = 1$, we have

$$\begin{aligned}
\exp W &= \prod_{T,R} \left(\mathbb{M}_R^T\right)^{\sigma_R^T} \left(\int_0^{\overline{\eta}_R^T} \left(Q_{Rj}^T\right)^{\rho} dG(j) \right)^{\sigma_R^T} \\
&= \rho^{\rho} (1-\rho)^{1-\rho} f_e^{\rho-1} \left(\overline{\eta}_1^1\right)^{-\rho} \left(\frac{\int_0^{\overline{\eta}_1^1} (\eta_j)^{\rho/(\rho-1)} dG(j)}{\int_0^{\overline{\eta}_1^1} (\eta_j)^{1/(\rho-1)} dG(j)} \right) \cdot \mathbb{I} \cdot \prod_{T,R} \left(\frac{\sigma_R^T}{u_R^T} \right)^{\sigma_R^T}.
\end{aligned}$$

Note that since $\overline{\eta}_R^T$ depends only on f_e, F_e and G, only the term $\mathbb{I} \cdot \prod_{T,R} \left(\sigma_R^T / u_R^T\right)^{\sigma_R^T}$ can vary with regional endowments.

G.7 Limited Factor Price Equalization

Since workers are imperfectly substitutable, they induce spillovers within firms, and consequently are not paid their marginal product.[59] Mirroring this, the equation for unit labor costs shows that regions with different skill distributions, say region R and R', typically cannot have both $c_R^T = c_{R'}^T$ and $w_R = w_{R'}$. However, factor price equalization for labor holds in a limited fashion. Summing across types in (3.6) implies

$$\text{Average Wages :} \quad \sum_i a_{R,i} w_{R,i} = \sum_T \alpha_L^T \sigma^T \mathbb{I},$$

so average wages are constant across regions. This is summarized as

Proposition 4. *Average wages are equalized across regions.*

Proposition 4 shows that while the model allows for heterogeneity of wages by worker type, general equilibrium forces still imply that factor price equalization holds *on average*. As is well known, this prediction will rarely hold in any real world setting, but can be understood in terms of factor augmenting technology differences (e.g. Trefler (1993)).

H Supplemental Summary Statistics and Empirical Results

UNICEF suggests that the typical Chinese primary school entrance age is 7 (Source: childinfo.org). Compulsory education lasts nine years (primary and secondary school) and ends around age sixteen. Figure A.1 illustrates the average years of schooling for the Chinese labor force, while Table A.13 displays the frequency of each worker type and their average monthly wages by Province.

[59] Such spillovers are internalized by firms in the model. The extent to which spillovers might also occur across industries is beyond the scope of this study, however see Moretti (2004) for evidence in the US context.

Figure A.1: Chinese Educational Attainment (2005)

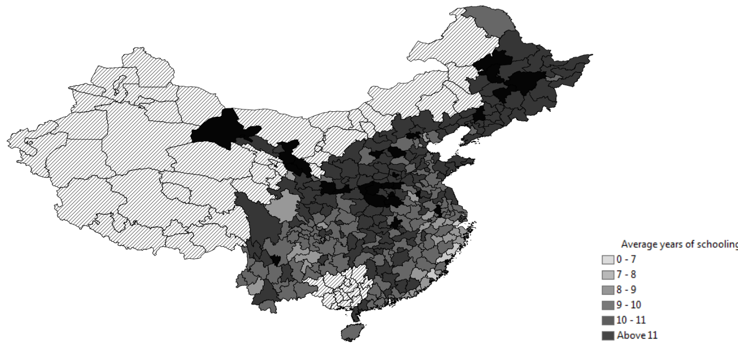


Table A.13: Educational and Wage Distribution by Province (2005)

Province	Fraction of Labor Force by Education				Avg Monthly Wage by Education			
	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above
Anhui	0.296	0.485	0.155	0.063	581	862	866	1210
Beijing	0.140	0.284	0.299	0.277	796	1059	1314	2866
Chongqing	0.272	0.408	0.227	0.093	582	820	872	1379
Fujian	0.348	0.453	0.146	0.052	695	942	1103	1855
Gansu	0.216	0.399	0.271	0.114	507	738	869	1135
Guangdong	0.327	0.362	0.231	0.080	748	967	1281	2719
Guizhou	0.292	0.478	0.162	0.069	572	758	925	1189
Hainan	0.328	0.334	0.259	0.080	532	694	894	1527
Hebei	0.230	0.515	0.190	0.066	515	793	832	1233
Heilongjiang	0.217	0.393	0.285	0.104	515	740	797	1096
Henan	0.229	0.428	0.234	0.109	487	675	714	1079
Hubei	0.271	0.384	0.264	0.081	541	757	809	1262
Hunan	0.263	0.444	0.229	0.063	634	828	889	1267
Jiangsu	0.314	0.400	0.210	0.076	758	994	1086	1773
Jiangxi	0.291	0.456	0.196	0.056	525	783	794	1240
Jilin	0.204	0.382	0.307	0.107	522	745	809	1163
Liaoning	0.250	0.410	0.219	0.120	576	822	848	1366
Shaanxi	0.203	0.406	0.277	0.114	497	731	805	1149
Shandong	0.288	0.441	0.203	0.068	602	823	863	1398
Shanghai	0.221	0.321	0.272	0.186	891	1155	1450	3085
Shanxi	0.169	0.520	0.221	0.089	502	872	857	1113
Sichuan	0.277	0.480	0.162	0.081	541	737	829	1477
Tianjin	0.258	0.321	0.285	0.136	995	1019	1074	1617
Yunnan	0.275	0.495	0.160	0.070	504	697	896	1542
Zhejiang	0.357	0.469	0.129	0.045	817	1097	1299	2333

H.1 Industrial Summary Statistics

Table A.14 presents the distribution of firms by industry and other descriptive statistics.

Table A.14: Manufacturing Survey Descriptive Statistics (2005)

				Share of				
Industry	# of firms	# of Regions	Avg # of workers	Female	White Collar	Export	State Equity	Foreign Equity
Beverage	2,225	155	219.20	.281	.114	.150	.107	.121
Electrical	12,241	166	201.58	.289	.106	.351	.030	.195
Food	3,807	171	193.98	.321	.091	.266	.060	.202
General Machines	15,727	195	152.68	.205	.117	.262	.047	.115
Iron & Steel	4,676	160	227.40	.148	.088	.101	.032	.056
Leather & Fur	4,852	89	320.70	.362	.036	.682	.005	.335
Precision Tools	2,702	68	214.89	.296	.180	.457	.063	.299
Metal Products	10,686	157	146.93	.233	.086	.332	.028	.161
Non-ferrous Metal	3,607	139	157.75	.186	.093	.180	.035	.093
Non-metal Products	15,347	259	195.57	.207	.090	.169	.059	.088
Paper	5,698	159	151.05	.269	.061	.127	.026	.131
Plastic	9,235	159	140.47	.298	.065	.327	.019	.235
PC & AV	6,699	90	402.04	.342	.120	.571	.038	.459
Specific Machines	7,816	167	176.76	.197	.154	.244	.072	.166
Textile	18,292	186	222.43	.390	.044	.406	.018	.168
Wood	3,629	133	137.04	.288	.050	.290	.025	.137

H.2 Provincial Summary Statistics

Table A.15: Descriptive Statistics by Province (2005)

	Manufacturing		Population Census			
	Firm	Avg	# of	# Region-	Monthly	Avg Yrs
Province	Count	Workers	Regions	Industries	Wage	School
Anhui	2,070	199.3	17	822	832	8.925
Beijing	2,976	137.3	2	128	1665	11.542
Chongqing	967	261.8	3	184	862	9.606
Fujian	6,314	206.5	9	504	945	8.170
Gansu	439	259.3	14	658	805	9.728
Guangdong	19,108	278.1	21	1269	1137	9.607
Guizhou	722	207.0	9	464	805	8.565
Hainan	86	162.6	3	151	830	9.772
Hebei	4,576	229.2	11	623	781	9.527
Heilongjiang	837	258.3	13	622	774	10.197
Henan	5,301	224.4	17	798	720	10.053
Hubei	2,266	236.3	14	742	789	9.731
Hunan	3,200	188.4	14	751	843	9.588
Jiangsu	20,028	168.5	13	756	1013	9.431
Jiangxi	1,363	237.3	11	556	766	9.208
Jilin	677	268.7	9	477	796	10.340
Liaoning	4,570	161.6	14	770	865	10.152
Shaanxi	1,070	318.5	10	548	787	10.068
Shandong	11,374	211.2	17	947	825	9.596
Shanghai	8,521	145.6	2	119	1577	10.569
Shanxi	1,056	375.5	11	619	847	9.895
Sichuan	2,858	234.0	21	887	800	9.149
Tianjin	2,236	186.1	2	128	1119	10.243
Yunnan	659	233.5	16	695	794	8.675
Zhejiang	23,965	143.3	11	629	1098	8.201

H.3 Verisimilitude of Census and Firm Wages

One of the main concerns about combining census data with manufacturing data is the representativeness of regional labor market conditions in determining actual wages within firms. It turns out they are remarkably good predictors of a firm's labor expenses. We construct a predictor of firm wages based on Census data and test it as follows: First, compute the average wages per prefecture. Second, make an estimate CensusWage by multiplying each firm's distribution of workers by the average wages of each type from the population census. Third, regress actual firm wages on CensusWage. The results are presented in Table A.16 of Appendix H.3. Not only is the R^2 of this predictor very high for each industry, but the coefficient on CensusWage is close to one in all cases, showing that one-for-one the census based averages are excellent at explaining the variation in the wage bill across firms.

Table A.16: Census Wages as a Predictor of Reported Firm Wages

Industry	Dependent Variable: ln (Firm Wage)					
	ln (Census Wage)	Std Dev	Constant	Std Dev	Obs	R^2
Beverage	1.052***	(0.0147)	-0.904***	(0.204)	2223	0.85
Electrical	1.018***	(0.0103)	-0.370***	(0.138)	12213	0.86
Food	1.032***	(0.0104)	-0.602***	(0.144)	3766	0.83
General Machines	1.020***	(0.0063)	-0.365***	(0.091)	15711	0.84
Iron & Steel	1.049***	(0.0082)	-0.777***	(0.116)	4663	0.87
Leather & Fur	0.982***	(0.0112)	0.116	(0.165)	4851	0.87
Precision Tools	1.018***	(0.0221)	-0.332	(0.308)	2689	0.83
Metal Products	1.012***	(0.0094)	-0.286**	(0.130)	10654	0.83
Non-ferrous Metal	1.054***	(0.0092)	-0.833***	(0.127)	3588	0.88
Non-metal Products	0.981***	(0.0085)	0.16	(0.122)	15329	0.80
Paper	1.012***	(0.0086)	-0.335***	(0.120)	5695	0.82
Plastic	1.015***	(0.0129)	-0.340**	(0.170)	9214	0.85
PC & AV	1.021***	(0.0172)	-0.354	(0.224)	6685	0.86
Specific Machines	1.036***	(0.0105)	-0.580***	(0.139)	7780	0.83
Textile	0.981***	(0.0060)	0.132	(0.084)	18281	0.86
Wood	0.965***	(0.0136)	0.309	(0.197)	3619	0.78

Standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

H.4 Firm Performance Characteristics and Productivity

Table A.17: Explaining Growth with Productivity

	Sales Growth Rate (2005-7)		
Productivity under Unit Cost method	-0.0924**		
	(0.0419)		
Productivity under L = 4 Types		-0.0648**	
		(0.0264)	
Productivity under L = Wage Bill			-0.0641**
			(0.0285)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	107,143	107,143	107,143
R-squared	0.027	0.027	0.027

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

Table A.18: Explaining Survival with Productivity

	Survival Rate (2005-7)		
Productivity under Unit Cost method	0.0184***		
	(0.00248)		
Productivity under L = 4 Types		0.0109***	
		(0.00165)	
Productivity under L = Wage Bill			0.00968***
			(0.00165)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	127,082	127,082	127,082
R-squared	0.023	0.022	0.022

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

H.5 Production Estimates by Method

Table A.19 compares the production coefficients under three measures of labor: unit labor costs, total wages, and employment of each worker type. In the latter case, the coefficient for type i workers are labeled α_L^i.

Table A.19: Second Stage Estimates vs Homogeneous Labor Estimates

	Unit Labor Cost			Total Wage Bill			Employment of Each Type					
Industry	α_L	α_K	α_M	α_L	α_K	α_M	α_L^1	α_L^2	α_L^3	α_L^4	α_K	α_M
Beverage	.18	.13	.62	.23	.06	.71	.07	.01	.07	.06	.07	.75
Electrical	.17	.19	.42	.34	.12	.47	.06	.02	.08	.12	.12	.53
Food	.15	.11	.65	.16	.06	.73	.07	.03	.09	.08	.12	.52
General Machines	.17	.14	.55	.25	.09	.61	.03	.01	.09	.03	.06	.76
Iron & Steel	.48	.09	.36	.25	.07	.68	.04	.03	.06	.08	.10	.66
Leather & Fur	.07	.18	.53	.27	.09	.55	.01	.07	.11	.05	.06	.71
Precision Tools	.17	.18	.44	.44	.08	.38	.02	.13	.07	.05	.09	.57
Metal Products	.31	.13	.40	.30	.12	.48	.09	.03	.05	.23	.11	.44
Non-ferrous Metal	.17	.10	.58	.17	.10	.65	.03	.04	.06	.02	.06	.71
Non-metal Products	.14	.19	.45	.20	.06	.67	.04	.04	.10	.07	.11	.55
Paper	.09	.25	.41	.28	.11	.52	.09	.02	.10	.08	.14	.47
Plastic	.22	.17	.36	.31	.13	.43	.04	.01	.08	.06	.09	.65
PC & AV	.15	.19	.39	.48	.14	.35	.11	.07	.08	.24	.16	.41
Specific Machines	.12	.20	.43	.31	.10	.48	.03	.01	.06	.13	.11	.53
Textile	.01	.14	.59	.29	.07	.56	.03	.09	.08	.08	.06	.58
Wood	.20	.14	.49	.23	.08	.62	.03	.07	.07	.08	.07	.63